DIRECT TESTIMONY OF
JOSEPH M. LYNCH, Ph.D.
ON BEHALF OF
DOMINION ENERGY SOUTH CAROLINA, INC.
DOCKET NO. 2019-184-E

Q. PLEASE STATE YOUR NAME AND BUSINESS ADDRESS.

A. My name is Joseph M. Lynch and my business address is 220 Operation Way, Cayce, South Carolina.

Q. BY WHOM ARE YOU EMPLOYED AND IN WHAT CAPACITY?

A. I am employed by Dominion Energy South Carolina, Inc. ("DESC" or the "Company")[1] as Manager of Resource Planning.

Q. PLEASE DESCRIBE YOUR DUTIES RELATED TO RESOURCE PLANNING IN YOUR CURRENT POSITION.

A. I am responsible for managing the department that produces DESC's forecast of energy, peak demand, and revenue. I also am responsible for overseeing the Company's load research program.

[1] South Carolina Electric & Gas Company ("SCE&G") changed its name to Dominion Energy South Carolina, Inc. in April 2019, as a result of the acquisition of SCANA Corporation by Dominion Energy, Inc. For consistency, I use "DESC" to refer to the Company both before and after this name change.

Q. DESCRIBE YOUR EDUCATIONAL BACKGROUND AND PROFESSIONAL EXPERIENCE.

A. I graduated from St. Francis College in Brooklyn, New York, with a Bachelor of Science degree in mathematics. From the University of South Carolina, I received a Master of Arts degree in mathematics, an MBA, and a Ph.D. in management science and finance. I was employed by the Company as Senior Budget Analyst in 1977 to develop econometric models to forecast sales and revenue. In 1980, I was promoted to Supervisor of the Load Research Department. In 1985, I became Supervisor of Regulatory Research where I was responsible for load research and electric rate design. In 1989, I became Supervisor of Forecasting and Regulatory Research, and in 1991, I was promoted to my current position of Manager of Resource Planning.

Q. HAVE YOU PREVIOUSLY TESTIFIED BEFORE THE PUBLIC SERVICE COMMISSION OF SOUTH CAROLINA ("COMMISSION")?

A. Yes. I have testified on numerous occasions before this Commission.

Q. WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A. The purpose of my testimony is to present certain analyses which support the development of the resource plan used to calculate DESC's avoided costs. The resource plan and the calculation of avoided costs are discussed in the Direct Testimony of Company Witness Mr. James Neely.

Q. WHAT ANALYSES ARE YOU PRESENTING?

A. I will discuss four analyses: 1) the impact of solar power on the need for capacity; 2) DESC's peak demand forecast; 3) DESC's reserve margin policy; and 4) a Loss of Load Expectation ("LOLE") study.

CONCERNING SOLAR PROFILES

Q. DID DESC UPDATE ITS ANALYSIS OF SOLAR PROFILES WHICH WAS PART OF THE 2018 FUEL DOCKET? IF SO, WHAT CHANGES WERE MADE IN THE ANALYSIS?

A. The updated analysis is contained in the study titled "The Capacity Benefit of Solar QFs 2018 Study" ("Solar Capacity Benefit Study") which is included as Exhibit No. ____ (JML-1). This study is essentially the same as the one presented in Docket No. 2018-2-E except that a composite solar profile was used instead of a single solar profile. The composite solar profile used in the report was the average of the actual generation of 7 single-axis tracking solar farms on the DESC system for the latest annual period available at the time, which was August 1, 2017, through July 31, 2018.

Q. WHAT WERE THE PRIMARY CONCLUSIONS MADE FROM THE SOLAR STUDY?

A. Consistent with last year's findings, the study again concluded that solar power cannot help to serve the system's winter peaking needs because the system typically peaks early in the morning before sunrise. Additionally, for most non-summer days, the system load peaks either before sunrise or after sunset, again with solar providing little or no support for serving daily peaks.

During the summer season, the study concludes that about 46% of the solar farm nameplate capacity will typically be provided to DESC's system during the summer peak days. This figure is higher than the 34% derived in last year's study which was not based on a composite solar profile. The 46% rating is based on the average solar output during the five highest summer peak load days. For the balance of summer days, the rating drops to 26%. Therefore, in developing a resource plan, DESC will consider 26% of the solar nameplate as a base resource available for the whole summer season with an additional 20% for a total of 46% available on summer peaking days.

Q. DOES THE UPDATED SOLAR CAPACITY BENEFIT STUDY INCLUDE AN ANALYSIS OF THE NUMBER OF DAYS PER YEAR WHEN THE DAILY PEAK IS UNAFFECTED BY SOLAR POWER?

A. Yes, the study contains an update to the same analysis made last year. The results are summarized in Table 1 below.

Table 1

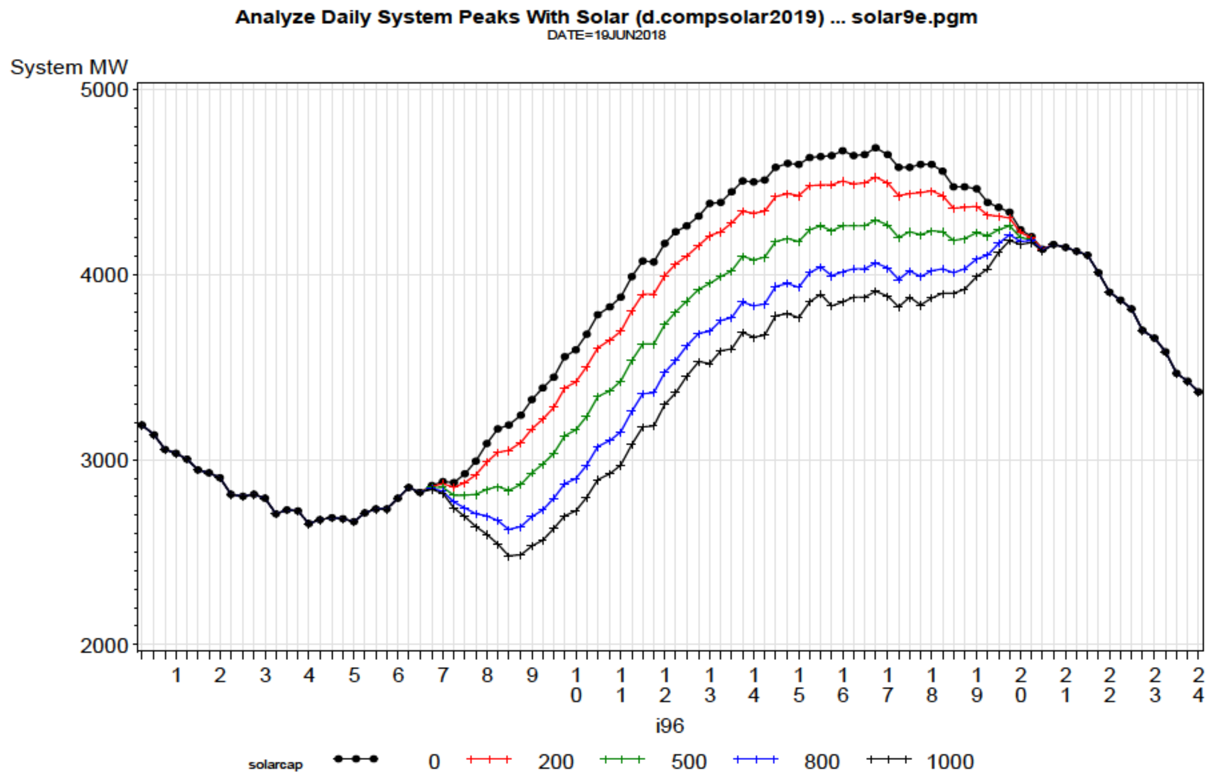
Number of Days by Month When a 100 MW Increment in Solar Has Zero Impact on the Peak Demand				
	Total Solar Capacity (in MW) After 100 MW Increment			
Month	200	500	800	1000
January	18	18	20	21
February	24	24	24	24
March	21	22	23	23
April	21	25	26	26
May	1	8	13	17
June	0	0	1	1
July	0	0	0	2
August	1	2	3	8
September	1	6	12	13
October	16	23	25	27
November	17	19	20	21
December	19	20	20	21

The table demonstrates that, as the amount of solar capacity increases, each increment of solar capacity affects the peak on fewer days. The last increment of 100 MW of solar capacity on the system, going from 900 MW to 1,000 MW of total solar capacity, leaves unaffected 163 daily peaks out of 212 days during the seven months of January through April and October through December. In other words, the last 100 MW increment of solar capacity on the system does not impact peak demand on approximately 77% of the days in those seven months. Even in the summer—when solar capacity affects the daily peak on most days—the last increment of 100 MW of solar capacity affects fewer daily peaks than previous increments.

Q. WHY DOES THE NUMBER OF DAYS WITH SOLAR AFFECTED PEAKS DECREASE AS THE TOTAL AMOUNT OF SOLAR CAPACITY IS ADDED TO THE SYSTEM?

A. The basic reason is that the time of the system peak can be changed by solar capacity. Particularly in summer, as more and more solar capacity is added to the system, the time of the system peak net of the solar output is shifted later and later in the day until it reaches the time of sunset, about 8 p.m., after which adding more solar capacity no longer affects the peak. This can be seen in Chart 1 below which shows the impact of different levels of solar on the day of last summer's system peak. This is more fully discussed in the study attached as Exhibit No. __ (JML-1).

Chart 1



Q. WHAT IMPACT FROM SOLAR HAS DESC SEEN ON RECENT WINTER PEAK DAYS?

A. Table 2 below shows the time of occurrence of the system peak in the last six winter seasons and only in 2018 has the peak occurred after sunrise allowing a non-zero impact from solar.

Table 2

Winter Peak Days on DESC's System		
Day of Peak	Peak MW	Time of Occurrence
January 07, 2014	4,717	7:30 a.m.
February 20, 2015	5,035	7:00 a.m.
January 19, 2016	4,451	7:00 a.m.
January 09, 2017	4,493	7:15 a.m.
January 05, 2018	4,776	8:00 a.m.
January 22, 2019	4,203	7:15 a.m.

Table 3 below shows the impact that various amounts of solar would have had during the 2018 winter peak.

Table 3

Impact of Solar on Peak Day January 5, 2018				
Solar Nameplate Facility Rating (MW)	Peak Load Less Solar Output (MW)	Additional Solar Production at the Peak (MW)	Cumulative Contribution of Solar Production at the Peak (MW)	Time of Effective Peak
0	4,776			8:00 a.m.
200	4,770	6	6	8:00 a.m.
500	4,762	8	14	7:30 a.m.
800	4,762	0	14	7:30 a.m.
1,000	4,762	0	14	7:30 a.m.

Table 3 shows that 500 MW of solar capacity would have only reduced the peak by 14 MW or 2.8% and would shift the peak of the net load to 7:30 a.m., at which time additional solar would have no effect.

Q. HAVE YOU CONSIDERED THE EFFECTIVE LOAD CARRYING CAPACITY ("ELCC") METHODOLOGY TO ESTABLISH THE FIRM CAPACITY VALUE OF SOLAR?

A. Yes, I performed the ELCC calculations because some interest has been expressed in this methodology. However, the ELCC value is just an application of the Loss of Load Expectation ("LOLE") technique which I explain later in my testimony is not appropriate for DESC. The Loss of Load Hours ("LOLH") metric is a reliability metric like LOLE but it uses 8,760 hours of load (the number of hours in a year) instead of the peak load on the 365 days of the year. I used the LOLH metric for this ELCC computation.

Q. PLEASE EXPLAIN THE ELCC METHODOLOGY AND PRESENT YOUR RESULTS.

A. There are basically three steps in calculating an ELCC value. The first step is to calculate the LOLH in the base case. I explain this in Exhibit No. ___ (JML-4). The second step is to create a change case by combining the solar profile with the base system load profile to create an adjusted load profile net of the solar output and then recalculate an LOLH. The LOLH in the change case will be lower than in the base case indicating more reliability. In the third step, either the loads are increased, or the capacity is decreased in the change case until the LOLH matches the base case LOLH. The resulting adjustment in load or capacity is the ELCC value of the solar profile since it results in an equivalent LOLH value to the base case.

The following table shows the ELCC results when 500 MW of solar is added to the system.

Table 3a

ELCC Results				
Step	Case	Description	Capacity	LOLH
1	Base	No Solar	5,310 MW	2.86
2	Change	500 MW Solar	5,310 MW	1.04
3	Adjusted	500 MW Solar	5,125 MW	2.86
		ELCC Value	185 MW	

The addition of 500 MW of solar represents 185 MW of firm capacity based on an equivalent LOLH or about 37% of nameplate capacity.

The following table shows the ELCC results when 500 MW of solar is added to the system on top of the first 500 MW.

Table 3b

ELCC Results				
Step	Case	Description	Capacity	LOLH
1	Base	500 MW Solar	5,125 MW	2.86
2	Change	1,000 MW Solar	5,125 MW	2.13
3	Adjusted	1,000 MW Solar	5,066 MW	2.86
		ELCC Value	59 MW	

As expected, the incremental value of solar decreases as more is added even when value is measured by the ELCC. The additional 500 MW of solar represents only 59 MW of firm capacity based on an equivalent LOLH. For the total of 1,000 MW, the ELCC value is 185 plus 59 or 244 MW or about 24% of nameplate capacity.

Q. HOW DO THESE RESULTS COMPARE TO YOUR ANALYSIS OF THE SOLAR IMPACT ON CAPACITY?

A. As shown in Table 7 on page 11 of Exhibit No. ___ (JML-1), the ELCC estimates are surprisingly close to the solar peak impacts on an average summer day, i.e. 24% for the ELCC and 26% based on a direct estimate of the solar impact on daily peaks. On the other hand, the ELCC result reflects just above half the solar impact measured on summer peak days as shown in Table 6 of Exhibit No.______(JML-1), i.e. 24% for the ELCC and 46% based on a direct estimate of solar impacts. Unfortunately, it does not matter how good or bad the ELCC estimates are in summer. DESC needs capacity in the winter and solar does not provide capacity on early winter mornings before sunrise when the system peaks nor during peak hours on most non-summer days when the system peaks before sunrise or after sunset.

Q. DOES A POSITIVE ELCC VALUE MEAN THAT SOLAR HAS CAPACITY VALUE THROUGHOUT THE YEAR?

A. No, absolutely not. Solar puts energy on the grid when the sun is shining, and the utility is required to accept it and dispatch the Company's system around it. In the context of determining the Company's avoided cost, however, "capacity value" means capacity costs that would be avoided as a direct result of a change in the resource plan caused by a solar purchase. Because solar purchases do not allow DESC to avoid any future capacity costs, this capacity value is zero.

Q. HAS DESC ANALYZED ANY SOLAR PROFILES THAT ARE MORE RECENT THAN PREVIOUSLY DISCUSSED?

A. Yes. Exhibit No.____(JML-1) includes an addendum that provides a preliminary analysis of a more recent composite solar profile. The updated profile was derived from 21 solar farms for the period June 1, 2018, through May 31, 2019. The addendum includes a preliminary analysis which, when completed, will be incorporated into our 2020 Integrated Resource Plan ("IRP").

Q. DID THE PRELIMINARY ANALYSIS BASED ON MORE RECENT SOLAR DATA VALIDATE DESC'S CONCLUSIONS REGARDING SOLAR POWER?

A. Yes, it did with the primary conclusion being that solar cannot help to serve our winter peak and therefore has zero capacity value.

DESC'S PEAK DEMAND FORECAST

Q. WHAT ARE THE PRINCIPAL RESULTS OF DESC'S PEAK DEMAND FORECAST STUDY?

A. As explained in "The Peak Demand Forecast" study attached as Exhibit No. ___(JML-2), the principal results are that DESC expects its winter peak demand to be higher than its summer peak demand over the 15-year planning horizon under normal weather conditions. Table 4 below shows the forecasted peaks by season using the industry convention that the winter season follows the summer season.

Table 4

wyr	_Total Internal Demand__ Summer	Winter	_Net Internal Demand__ Summer	Winter	_Demand Response__ Summer	Winter
2019	4,883	4,964	4,639	4,749	-244	-215
2020	4,933	5,008	4,688	4,792	-245	-216
2021	4,979	5,039	4,733	4,822	-246	-217
2022	5,019	5,078	4,772	4,860	-247	-218
2023	5,058	5,100	4,810	4,882	-248	-218
2024	5,084	5,140	4,835	4,921	-249	-219
2025	5,124	5,183	4,874	4,963	-250	-220
2026	5,170	5,228	4,919	5,007	-251	-221
2027	5,213	5,268	4,961	5,046	-252	-222
2028	5,257	5,308	5,003	5,085	-254	-223
2029	5,297	5,348	5,042	5,124	-255	-224
2030	5,340	5,391	5,084	5,166	-256	-225
2031	5,382	5,434	5,125	5,208	-257	-226
2032	5,426	5,475	5,168	5,248	-258	-227
2033	5,467	5,518	5,208	5,290	-259	-228
2034	5,510	5,558	5,250	5,329	-260	-229
2035	5,553	5,598	5,292	5,368	-261	-230
2036	5,596	5,638	5,334	5,407	-262	-231
2037	5,639	5,680	5,375	5,448	-264	-232

The total internal demand, also referred to as the gross peak, represents the system peak demand before dispatching any demand response ("DR") resources. The net internal demand, also known as the net peak or firm peak demand, represents the peak demand after all DR resources are dispatched. The DR forecast represents the Company's existing DR resources.

Q. HOW DOES DESC FORECAST ITS SEASONAL PEAK DEMANDS?

A. The details of the forecasting process are explained more fully in the study attached as Exhibit No. ___(JML-2). However, the basic methodology uses the customer and energy sales forecast as the driver for growth and uses the load characteristics of each customer class captured in the Company's Load Research Program to develop the resulting peak demand. After this base level of demand is calculated, adjustments are made to the forecast to account for the incremental impacts of energy efficiency (both from Company programs and federal mandates) and incremental net energy metering on the system. Table 5 below shows the process to develop the base forecast for the residential, commercial and industrial classes in the next few seasons.

Table 5

Components in the Base Peak Demand Forecast				
Season	**Driver**	**Load Characteristic**	**4-Hour Factor**	**Base Peak Forecast**
Residential 2019 Summer	634,054 Customers	3.310 kW per Customer	1.0098	2,119 MW
Residential 2019/2020 Winter	643,719 Customers	3.973 kW per Customer		2,558 MW
Commercial 2019 Summer	97,221 Customers	15.887 kW per Customer	1.0098	1,560 MW
Commercial 2019/2020 Winter	98,116 Customers	13.856 kW per Customer		1,359 MW
Industrial 2019 Summer	5,908.3 GWh	1.047 kW per kWh	1.0098	713 MW
Industrial 2019/2020 Winter	5,986.2 GWh	0.904 kW per kWh		618 MW

The 4-hour factor applied in the summer season converts the forecast for the 4-hour band of hours, i.e., 2 p.m. to 6 p.m., to a one-hour basis. The winter peak does not need to be converted since it is projected on a one-hour basis. The calculation for the residential and commercial classes is straightforward. For example, in the case of the residential 2019 summer, the calculation is:

$$634{,}054 * 3.310 * 1.0098 = 2{,}119{,}286 \text{ kW} = 2{,}119 \text{ MW}$$

For the industrial class, the number of hours in the year comes into play. For example, in the case of the industrial 2019/2020 winter, the calculation is:

(5,986.2/ (8,760/1,000)) * 0.904 = 618 MW.

It may be worth noting that the kW per kWh load characteristic can be referred to as the demand ratio and is equal to the reciprocal of the load factor.

Q. WHY DOES DESC PROJECT ITS WINTER PEAK TO BE HIGHER THAN ITS SUMMER PEAK?

A. The prominence of the winter peak demand relative to the summer peak demand is a consequence of changes in customer usage patterns resulting from energy efficiency and conservation having different seasonal impacts. For example, based on the Company's load research studies, the kW per customer impact on the summer peak demand has decreased from about 3.804 kW prior to the Great Recession[2] to about 3.310 kW today while the winter peak demand decreased from about 4.132 kW to about 3.973 kW. This reflects an approximate 13% decrease in summer peak demand and only about a 4% decrease in winter peak demand. For the average commercial customer, the decrease is about 10% in summer from 17.724 kW per customer to 15.887 kW and only about 3% in winter from 14.281 kW to 13.856 kW per customer. This data clearly demonstrates there are more effective opportunities to conserve electricity in summer than winter.

[2] The National Bureau of Economic Research sets the dates of the Great Recession as beginning in December 2007 and ending in June 2009.

Q. THE PROJECTED WINTER PEAKS AND SUMMER PEAKS ARE VERY CLOSE. WOULD SIGNIFICANT CHANGES NEED TO BE MADE TO THE ASSUMPTIONS IN THE FORECAST TO PRODUCE A SUMMER PEAK FORECAST GREATER THAN THE WINTER PEAK FORECAST?

A. No. The summer peak forecast and the winter peak forecast are close. For example, for the 2020 planning year, i.e., with the winter season following the summer, the projected winter peak demand is 104 MW larger than the summer peak and only 61 MW for the calendar year. This difference could easily reverse with a small change in customer load characteristics. For example, if the residential class contributes 3.410 kW per customer instead of 3.310 kW, the summer forecast would increase by about 65 MW while if the winter contribution decreased from 3.973 kW per customer to 3.873 kW, the winter demand would decrease by about 65 MW. Under these circumstances, the summer peak demand would be larger than the winter peak demand. Similar what-if calculations can be made for the commercial class. Therefore, it is not unreasonable to imagine that some of the significant drop in kW per customer contribution observed in the summer for both the residential and commercial classes might reverse in the near future as the economy improves.

<u>DESC'S RESERVE MARGIN POLICY</u>

Q. WHAT IS DESC'S CURRENT RESERVE MARGIN POLICY USED IN DEVELOPING ITS RESOURCE PLAN?

A. Table 6 below summarizes DESC's reserve margin policy.

Table 6
Minimum Reserve Margin as Percent of Seasonal Peak Demand

	SUMMER	WINTER
Base Level	12%	14%
Peaking Level	14%	21%
Increment for Peaking	2%	7%

The Commission accepted these reserve margins in Order No. 2018-322(A).

Q. HAS DESC MODIFIED THE RESERVE MARGIN STUDY PRESENTED IN THE 2018 FUEL DOCKET?

A. Yes. The updated study titled "2018 Reserve Margin Study" is attached as Exhibit No. __ (JML-3). This study differs from last year in that more analysis is provided to establish the winter and summer peak demand risk related to extreme weather. Last year, a single quadratic regression equation, one in each season, was used to estimate the weather risk. Because of this, questions were asked about the appropriateness of using a quadratic formulation and of using all heating or cooling days in the season for regression estimation. To address these questions head on, this year's study developed three separate equations for each season: a quadratic equation using all the heating or cooling days in the season; a quadratic formula using a restricted number of days; and finally, a linear equation using a restricted number of days.

Q. WHAT WERE THE RESULTS?

A. Table 7 below shows the three components that make up the reserve margin, i.e., the VACAR operating reserves, the reserves for the demand-side risk, and the reserves for the supply-side risk.

Table 7

Reserve Margin for Summer and Winter Peak Periods		
	Summer	**Winter**
VACAR Operating	**200**	**200**
Demand-Side Risk	**245**	**556**
Supply-Side Risk	**234**	**223**
Total Reserve MW	**679**	**979**
Normal Peak Demand	**4763**	**4852**
Reserve Margin %	**14.3%**	**20.2%**
Reserve Margin Policy	**14%**	**21%**

The results of the study support the continued use of a 14% minimum reserve margin in summer and 21% in winter.

Q. WHAT WERE THE ESTIMATES OF DEMAND-SIDE RISK FROM THE DIFFERENT FORMULATIONS OF STATISTICAL ESTIMATION?

A. Table 8 below shows the estimated demand risk by season based on all three equations.

Table 8

Demand Risk Related to Extreme Weather (MW)		
	Summer	**Winter**
Quadratic, All Days	**245**	**556**
Quadratic, Restricted Days	**252**	**617**
Linear, Restricted Days	**292**	**509**

Even though the results using the quadratic regression model on all heating or cooling days were used to develop DESC's reserve margin, the other formulations clearly do not provide a significantly different estimate.

Q. THE WINTER DEMAND SIDE RISK IS MUCH HIGHER THAN SUMMER. CAN YOU CORROBORATE THAT LEVEL OF RISK IN WINTER?

A. Yes. DESC's demand forecasting methodology and class load characteristics can be used to corroborate this level of risk in the winter. As previously discussed, DESC expects residential customers to contribute about 3.973 kW per customer at the time of winter peak demand and commercial customers to contribute about 13.856 kW. In 2003, DESC experienced a very cold winter and our load research program estimated the residential contribution to peak then to be 4.649 kW per customer and the commercial contribution, 15.391 kW. Table 9 below shows the potential demand risk if next winter is very cold and residential and commercial customers respond in a similar manner as they did in 2003.

Table 9

2019 Demand-side Winter Weather Risk				
	Customers	2003 kW per Customer	Normal kW per Customer	Risk Estimate
Residential	643,719	4.649	3.973	435 MW
Commercial	98,116	15.391	13.856	151 MW
Total Demand Risk				**586 MW**

The demand-side winter weather risk estimate developed here using load research data of 586 MW is reasonably close to the statistical estimate of 556 MW used in the reserve margin analysis. When presenting the demand forecast, I stated that conservation and energy efficiency seemed to have reduced the residential demand by about 4% and the commercial demand by 3% since the Great Recession. Even taking this into consideration, the winter demand-side risk used in the reserve margin is reasonable. Here is that calculation using adjusted load research characteristics:

435 MW *(1.00-0.04) + 151 MW * (1.00-0.03) = 564 MW.

The result of 564 MW is close to the level used of 556 MW.

Q. USING THE DEMAND SIDE RISK AND THE SUPPLY SIDE RISK DISCUSSED ABOVE, CAN YOU CALCULATE THE PROBABILITY OF THE LOAD EXCEEDING THE AVAILABLE CAPACITY?

A. Yes, I can. The probability distribution of demand side risk is summarized in Table 2 of Exhibit No. ___(JML-3) and the probability distribution of supply side risk in Table 3. Using the Convolution Formula from statistical theory, the joint probability distribution can be calculated which will combine both sources of risk. Assuming a 21% reserve margin in the winter, the resulting probability that the winter peak will exceed our winter capacity is 3.2%. The probability of load exceeding capacity at least once in the next 10 years is about 28%. In the event DESC experiences a capacity problem, there is no certainty that one or more of our neighboring utilities will not also be experiencing high demand and therefore unable to provide capacity.

Q. WHAT IS THE PROBABILITY OF NOT HAVING SUFFICIENT CAPACITY TO MEET YOUR VACAR REQUIREMENT OF 200 MW?

A. The probability of not having enough capacity to meet the customer load and our VACAR requirement of having 200 MW of capacity in reserve is about 7.5%, again assuming a 21% winter reserve margin. The probability of not meeting the requirement in at least one of the next ten years is 54%.

CONCERNING DESC'S LOSS OF LOAD EXPECTATION STUDY

Q. DID DESC RELY ON A LOSS OF LOAD EXPECTATION ("LOLE") STUDY TO ESTABLISH ITS RESERVE MARGIN POLICY? IF NOT, WHY PRESENT IT IN THIS DOCKET?

A. DESC has made LOLE calculations for many years and reported the results in its IRPs over those years. However, DESC does not rely on LOLE calculations to establish its reserve margin policy but has reported them as support of its policy.

A formal LOLE study is being presented in this docket and is attached as Exhibit No. __ (JML-4) because LOLE is prevalent in the industry for establishing a reserve margin and a desire for these LOLE calculations was expressed in last year's fuel docket.

Q. WHAT WAS THE GOAL OF THE LOLE STUDY AND HOW DID DESC GO ABOUT CONDUCTING THE STUDY?

A. The goal of the study was to develop the functional relationship between the LOLE index and the system reserve margin. Once this function was estimated, it is a simple matter to calculate the level of reserve margin associated with an LOLE=0.1. An LOLE of 0.1 represents an outage expectation of 1 day in 10 years or stated differently, 0.1 days in 1 year, and it is the generally accepted level of risk tolerance in the industry.[3] As described in the attached study, DESC analyzed 15 years of load data, normalizing the load data to 2019 forecasted levels and calculating the LOLE associated with each reserve margin in the range of 12 to 25% at 0.5% intervals. The load data was adjusted in two ways making for two LOLE sensitivities. One method of adjustment, "the Peak Method," scaled the daily peaks in 2004 through 2018 to produce seasonal peaks equal to those forecasted for 2019 while the second approach, "the Energy Method," scaled the historical load data so it had the same annual energy as 2019. The two approaches produced similar results.

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[3] See "Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning", NERC, March 2011, page 14.

Q. WHAT ARE THE RESULTS OF THE LOLE STUDY AND WHAT DO THEY IMPLY FOR DESC'S RESERVE MARGIN POLICY?

A. For each of the 15 years in the study, the reserve margin producing an LOLE=0.1 for that year was computed. Table 10 below summarizes the results for the two variations of peak load adjustment.

Table 10

Reserve Margin Distributions for LOLE=0.1 for Years 2004-2018			
	Minimum	Median	Maximum
Peak Method	16.6%	18.2%	20.5%
Energy Method	14.8%	17.2%	21.3%

For the Peak Method of adjustment, one year produced a minimum value of 16.6% and one year a maximum value of 20.5%. For the Energy Method, the range was 14.8% to 21.3%. Each year was similar in the sense of having the same seasonal peak demands or the same annual energy but dissimilar in that each yearly profile was different as a result of the weather patterns and other conditions occurring in that particular year. Thus, for an LOLE=0.1, these results suggest that the DESC system requires a reserve margin between a low value of 14.8% and a high value of 21.3% with an average median value of 17.7%.

Since the LOLE methodology uses all days of the year and the LOLE index is a risk measure for the entire year, it should be compared to DESC's base level of reserve margin, i.e., the 14% for winter season and 12% for summer. DESC's base reserve margin falls below the LOLE value of 17.7% and therefore is riskier than the LOLE standard of 0.1 or one day in 10 years criterion. In fact, using a formula derived in Exhibit No. ______(JML-4) relating reserve margin to LOLE index, a 14% reserve margin can be shown to be equivalent to an LOLE=0.3 on DESC's system on average. That means a risk level of 3 days in 10 years which is riskier than 1 day in 10 years. However, DESC believes that its additional peak reserve resources, which mostly consist of demand response programs, will mitigate some of that added risk.

Q. CAN THE LOLE METHODOLOGY BE USED TO ADDRESS PEAK DEMAND RISK, THAT IS, RISK FROM DEMAND SPIKES RELATED TO ABNORMAL WEATHER?

A. No. The LOLE methodology addresses average risk for the entire year and an unacceptable risk level on the peak day can be hidden by the summary result for the year. As shown in Exhibit No.____(JML-4), a simple experiment of adding a spike of 500 MW to the annual peak and then computing the LOLE can illustrate the problem. Attached are the results of this experiment.

Experiment to Analyze Peak Load Increase and Risk			
	Peak Load	**Capacity**	**LOLE**
Step 1: Calculate base value of LOLE	**4,964**	**5,900**	**0.11235**
Step 2: Add 500 MW to peak day	**5,464**	**5,900**	**0.23616**
Step 3: Increase Capacity to Restore LOLE	**5,464**	**6,095**	**0.11234**

The experiment shows that the combination of a peak load and capacity of 4,964 MW and 5,900 MW is equivalent in terms of LOLE to a combination of peak load and capacity of 5,464 MW and 6,095 MW. The LOLE method therefore suggests that an increase of 195 MW of capacity (6,095-5,900=195) is sufficient to offset the demand risk created by an additional 500 MW in load (5,464-4,964=500) which is clearly unreasonable and unacceptable. This LOLE experiment yields these results because, in making the LOLE calculations, every day of the year is considered to be a little less risky because of the additional 195 MW of capacity. The sum of the reduced risk as measured by the LOLE index on all these days therefore makes it appear 195 MW of additional capacity would be sufficient to offset the unacceptable 500 MW risk remaining on the peak day. The logical conclusion to draw from these results is that, if you are concerned about extreme weather spikes in seasonal peaks, the related risk must be analyzed directly as DESC has done in its methodology and not by a method that summarizes risk for the entire year as LOLE does.

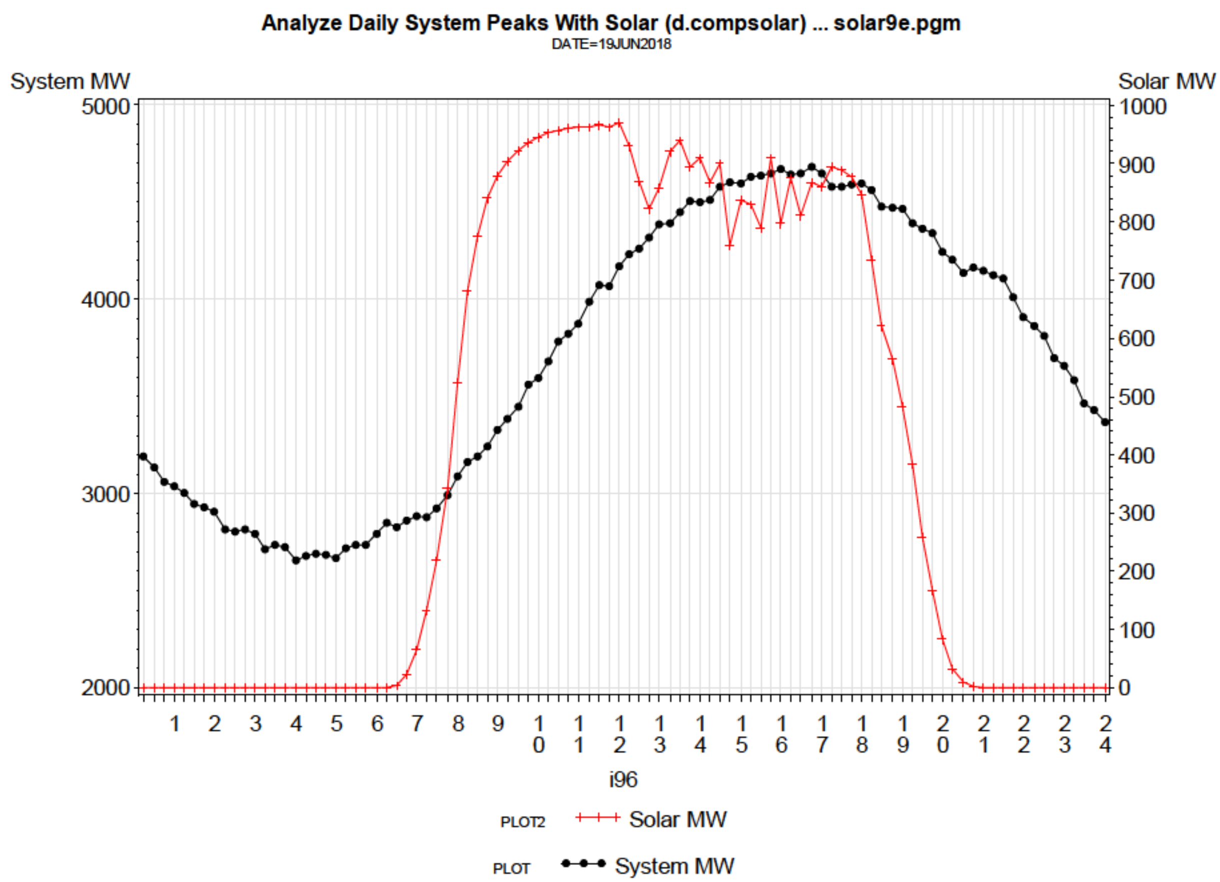
Q. DOES THIS CONCLUDE YOUR DIRECT TESTIMONY?

A. Yes.

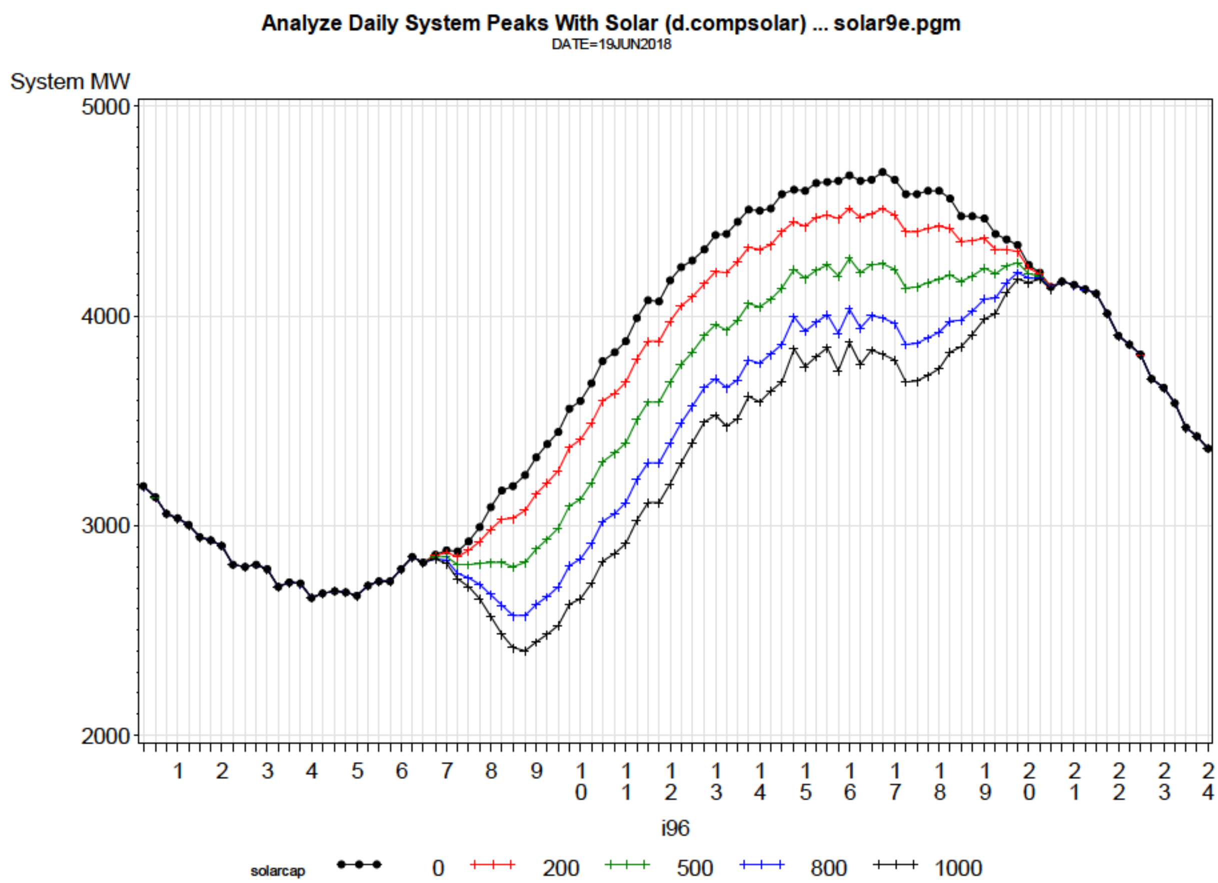
The Capacity Benefit of Solar QFs

2018 Study

Introduction: The following chart compares the system and solar profiles on June 19, 2018, the summer peak day of 2018. The system load is measured on the left vertical axis and the solar on the right. The solar profile used throughout this report is the average of the actual generation of 7 single-axis tracking solar farms on the Dominion Energy South Carolina, Inc. ("DESC") system for the latest annual period available which was August 1, 2017, through July 31, 2018. The solar profile is scaled to a maximum capacity of 1,000 MW for illustration. One of the first points to notice is that, during this summer day, the solar profile is positive for about 13 hours, from 7:00 a.m. (0700 hours) until about 8:00 p.m. (2000 hours). The system peak is 4,683 MW occurring at 4:45 p.m. (1645 hours) and by 8:00 p.m. (2000 hours) it decreases to about 4,100 MW when solar stops producing power. This means that no matter how much solar capacity is added to the system on this day the maximum effect will be to reduce the peak by about 583 MW (=4,683-4,100). This is because the solar output will be zero at about 8:00 p.m. (2000 hours) and therefore could not reduce the load below 4,100 MW.



The following chart compares the system load without the addition of solar to the system load that results when 200, 500, 800 and 1,000 MW of solar capacity are subtracted from the original system load. Referring to the chart below, the impact of increasing amounts of solar capacity on the system load can be seen visually.



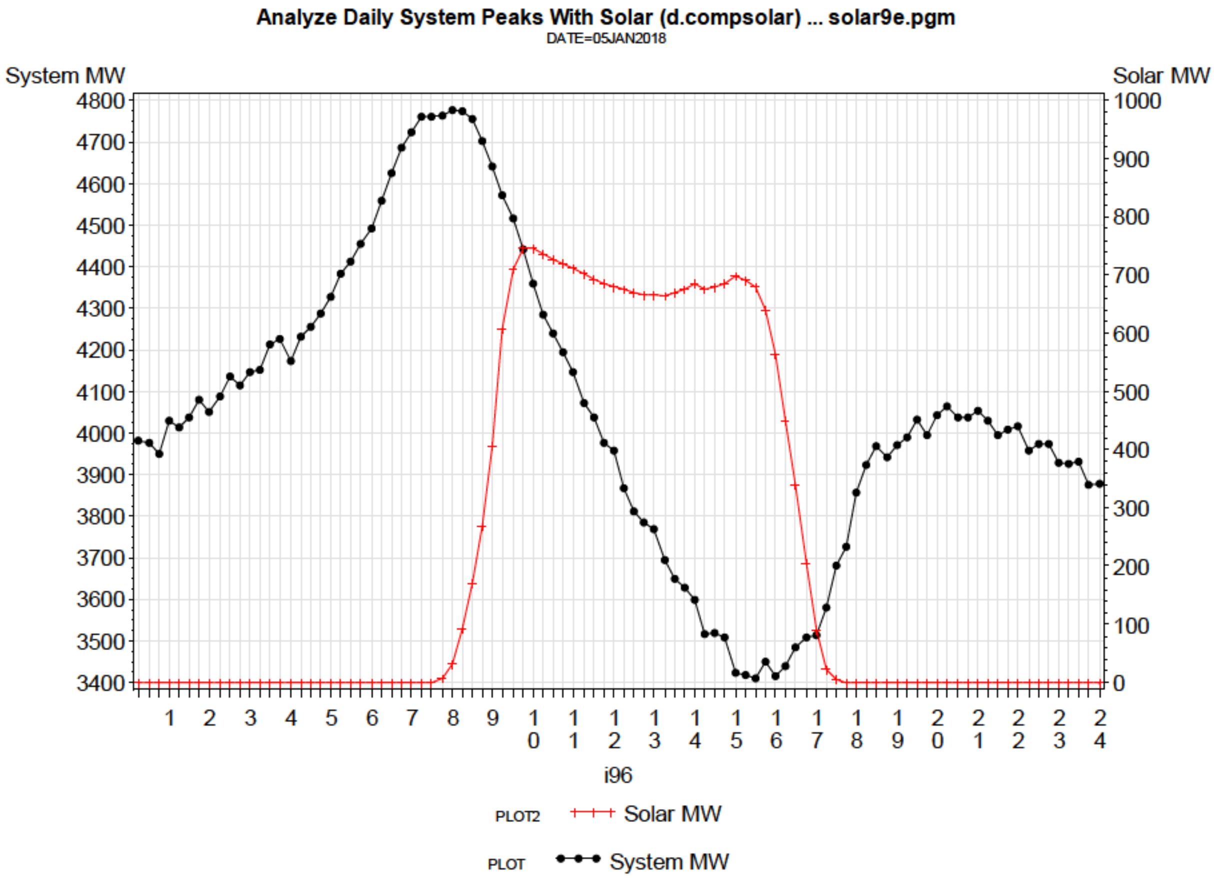
The following Table 1 shows the numerical impact on the peak demand as well as the incremental and cumulative change in peak demand.

Table 1

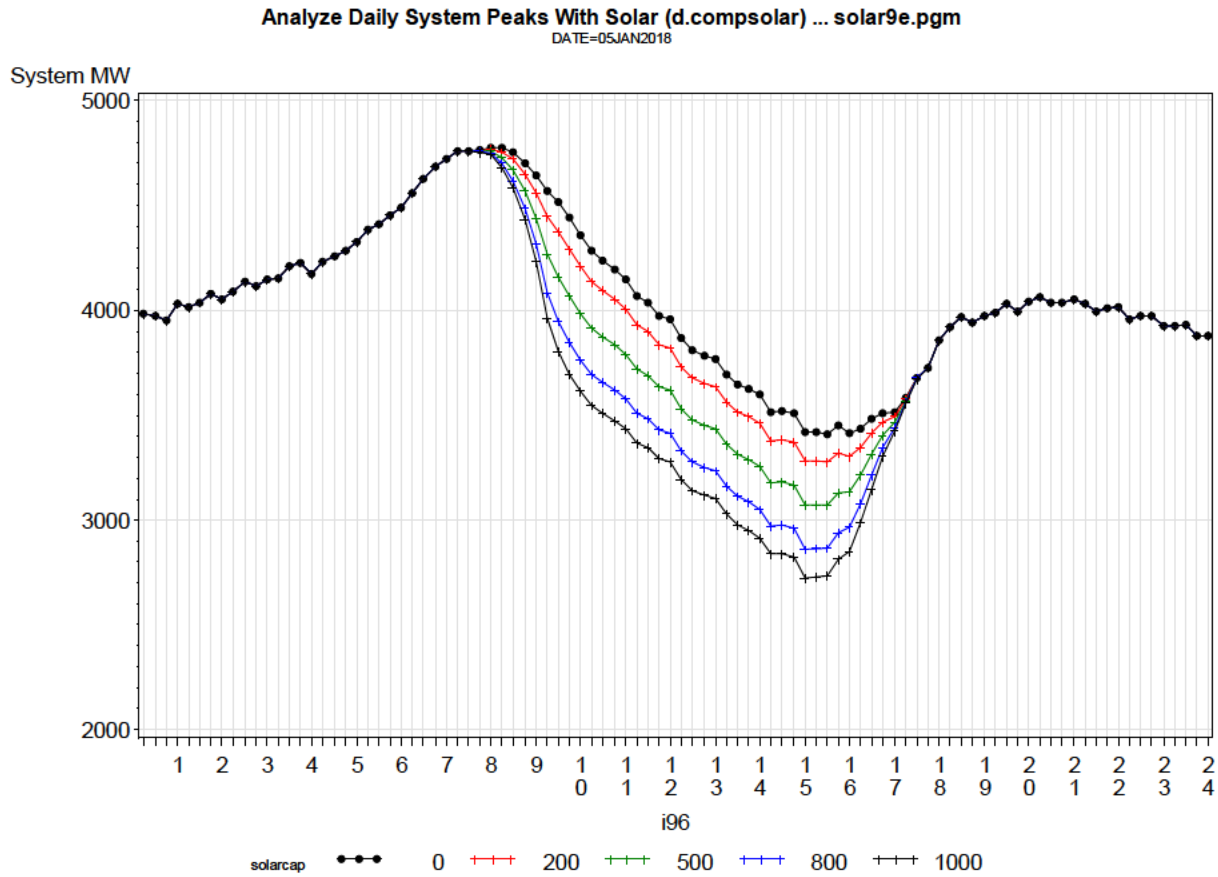
Impact of Solar on Peak Day June 19, 2018				
Solar Nameplate Facility Rating (MW)	Peak Load Less Solar Output (MW)	Additional Solar Production at the Peak (MW)	Cumulative Contribution of Solar Production at the Peak (MW)	Time of Effective Peak
0	4,683			4:45 p.m.
200	4,512	172	172	4:00 p.m.
500	4,272	239	411	4:00 p.m.
800	4,205	67	478	7:45 p.m.
1,000	4,174	32	509	8:15 p.m.

For example, the first 200 MW of solar capacity will reduce the peak demand by 172 MW while the last 200 MW, that is, going from 800 to 1,000 MW, will only reduce the peak demand by 32 MW. The change in the time of the peak occurrence helps explain this result. The time of the peak changes from 4:45 p.m. to 8:15 p.m.

A similar discussion can be made for a winter day. The following chart shows the system and solar profile for January 5, 2018, the winter peak day of 2018. It is instructive to note that the solar profile is positive for about 10 hours from about 7:45 a.m. (0745 hours) until about 5:30 p.m. (1730 hours). Since the system peaked at 8:00 a.m. (0800 hours) on this day, the solar impact was modest, only 31 MW. A 1,000 MW solar farm would only change the peak by 14 MW because the time of the peak would change from 8:00 a.m. to 7:30 a.m.



As was shown for the summer peak day, the following chart compares the system load without the addition of solar to the system load that results when 200, 500, 800 and 1,000 MW of solar capacity are subtracted from the original system load.



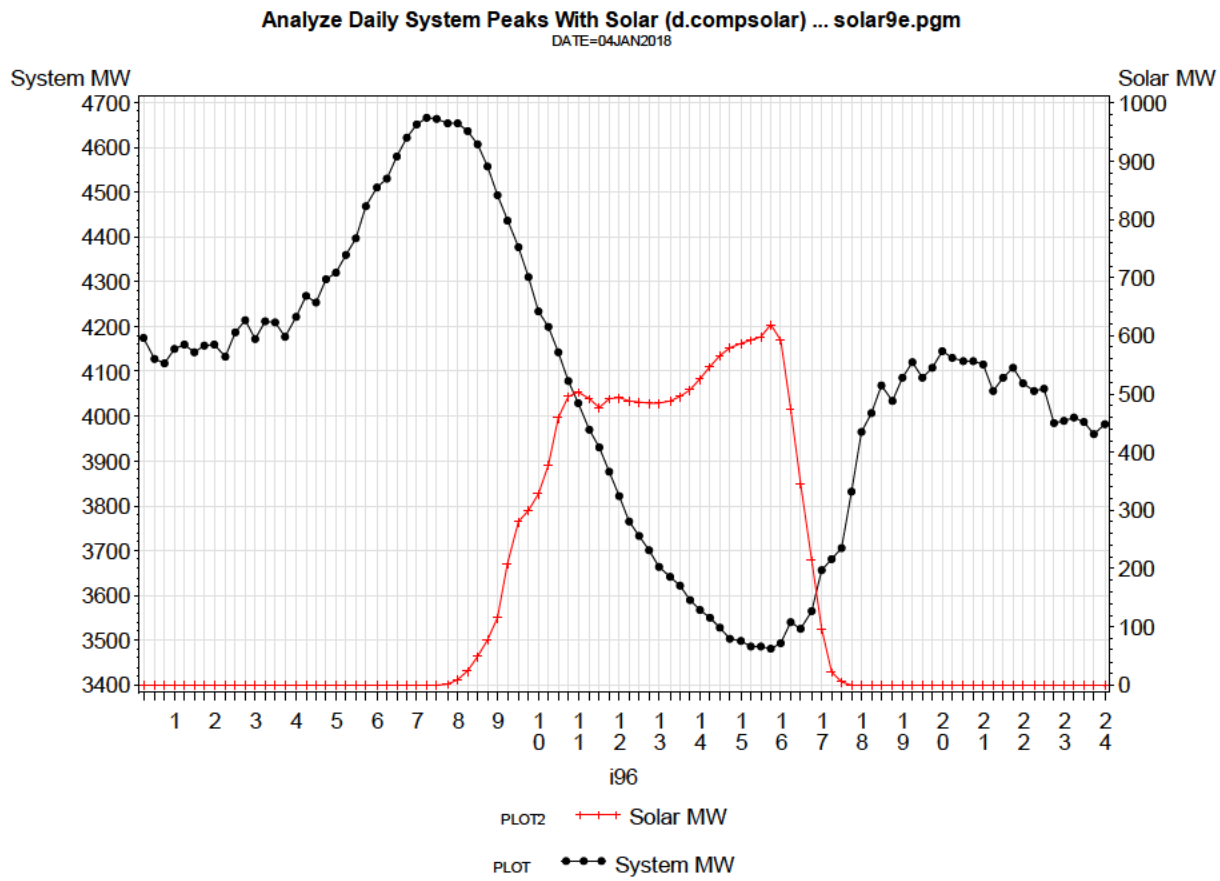
The following Table 2 displays the information in tabular form.

Table 2

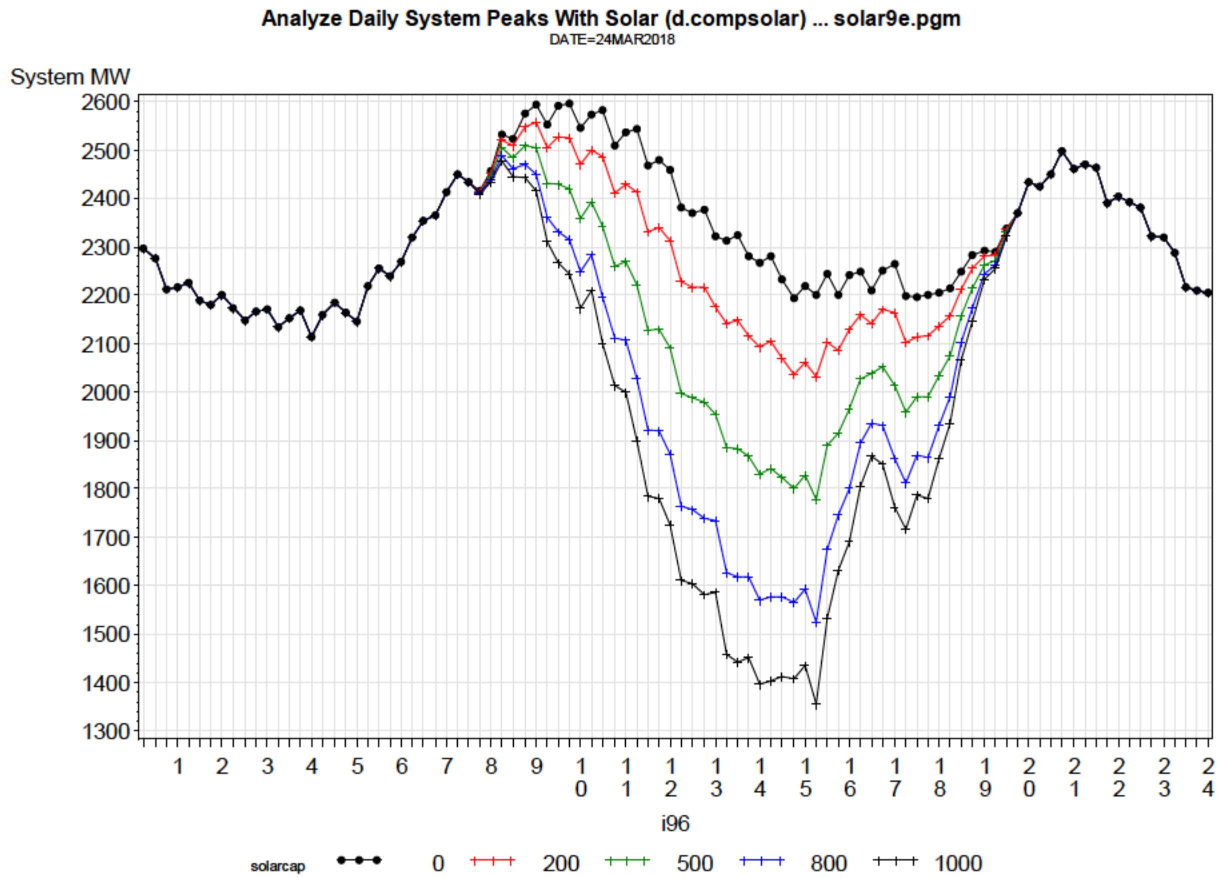
Impact of Solar on Peak Day January 5, 2018				
Solar Nameplate Facility Rating (MW)	Peak Load Less Solar Output (MW)	Additional Solar Production at the Peak (MW)	Cumulative Contribution of Solar Production at the Peak (MW)	Time of Effective Peak
0	4,776			8:00 a.m.
200	4,770	6	6	8:00 a.m.
500	4,762	8	14	7:30 a.m.
800	4,762	0	14	7:30 a.m.
1,000	4,762	0	14	7:30 a.m.

Table 2 shows that the first 500 MW of solar capacity reduces the system peak demand by 14 MW while the next increment of 500 MW has no effect after rounding. To one decimal place the impact is 0.1 MW.

The following chart shows the system and solar profile on the day prior to the peak day, i.e., January 4, 2018. On January 4, 2018, the system peak occurred at 7:30 a.m. when the solar output was zero. Consequently, no matter how much solar is added, even 1,000 MW, there would be no reduction in the system peak on this day.



The following chart shows a shoulder day on the system in which the morning peak is much lower than what is experienced on very cold winter mornings. The day is March 24, 2018, and the impact of solar on the system load can be seen to be very dramatic when the steep ramping is considered, down in the morning and up in the afternoon.



Study Results: The previous charts and discussion are useful to understand what happens when solar capacity is added to the system but to have a complete picture it is necessary to look at all the days of the year. It has been shown that for some days the impact of solar on the need for capacity is zero. The Company is interested in the impacts of incremental levels of solar and it has been shown that as more solar capacity is added to the system, the incremental effects decrease. The following Table 3 displays the number of peak days affected by increments of solar in 100 MW steps. For example, if 100 MW of solar are added to DESC's system during the period of this study, there would be 18 days in January on which the peak demand is not changed; 24 days in February, 20 in March, etc. However, if there exists 900 MW of solar already on the system and 100 MW more is added to produce a total of 1,000 MW, this last 100 MW will leave the peak demand unaffected on 21 days in January, 24 days in February, 23 days in March, etc.

Table 3

Number of Days By Month When a 100 MW Increment in Solar Has Zero Impact on the Peak Demand										
	Amount of Solar Capacity on the System After the 100 MW Increment									
Month	100	200	300	400	500	600	700	800	900	1000
1	18	18	18	18	18	18	19	20	20	21
2	24	24	24	24	24	24	24	24	24	24
3	20	21	21	21	22	22	22	23	23	23
4	9	21	23	24	25	25	25	26	26	26
5	0	1	2	6	8	13	13	13	15	17
6	0	0	0	0	0	0	1	1	1	1
7	0	0	0	0	0	0	0	0	0	2
8	0	1	1	1	2	2	2	3	8	8
9	1	1	2	5	6	10	10	12	13	13
10	14	16	19	21	23	24	24	25	26	27
11	15	17	19	19	19	20	20	20	21	21
12	19	19	19	20	20	20	20	20	20	21
Total	120	139	148	159	167	178	180	187	197	204

It appears that for 7 months of the year, solar will not affect the daily peak demand on most of the days of the month. However, for 3 months, i.e., for June through August, solar will impact the peak demand on most days of the month.

Solar Impact in Winter: Consideration of the winter months October through April supports the conclusion that solar has zero capacity value in winter. There are 212 days in these 7 months and on 163 of those days, the last 100 MW increment of solar reaching a total of 1,000 MW of solar capacity has no impact on the system peak demand reflecting about a 77% fail ratio.

It is useful to note the time of the system peak demand in the last 5 winter seasons. Table 4 below contains this information.

Table 4

Winter Peak Days on DESC's System		
Day of Peak	Peak (MW)	Time of Occurrence
January 07, 2014	4,717	7:30 a.m.
February 20, 2015	5,035	7:00 a.m.
January 19, 2016	4,451	7:00 a.m.
January 09, 2017	4,493	7:15 a.m.
January 05, 2018	4,776	8:00 a.m.

On the four winter peak days when the peak demand occurred at or before 7:30 a.m., the presence of solar capacity would not have helped serve the peak load. The following Table 5 shows the impact that various amounts of solar would have on the 2018 winter peak.

Table 5

Impact of Solar on Peak Day January 5, 2018				
Solar Nameplate Facility Rating (MW)	Peak Load Less Solar Output (MW)	Additional Solar Production at the Peak (MW)	Cumulative Contribution of Solar Production at the Peak (MW)	Time of Effective Peak
0	4,776			8:00 a.m.
200	4,770	6	6	8:00 a.m.
500	4,762	8	14	7:30 a.m.
800	4,762	0	14	7:30 a.m.
1,000	4,762	0	14	7:30 a.m.

Table 5 shows that 500 MW of solar capacity would have only reduced the peak by 14 MW or 2.8% and would shift the peak of the net load to 7:30 a.m. at which time additional solar would have no effect.

Solar Impact in Summer: The tables below show the results of the summer analysis. Table 6 shows the solar impact on the five highest peak days of the summer. For 1,000 MW of solar added to the system, the average daily peak demand is reduced approximately 46% or about 461.6 MW. The last 100 MW of solar capacity, that is, the incremental impact when solar capacity is increased from 900 MW to 1,000 MW, reduces the peak demand by 14.5 MW on average which can also be expressed as 14.5%.

Table 6

Average Impact of Solar Capacity On 5 Highest Peak Summer Days				
Solar Capacity	Nbr Days	Peak Reduction MW	% Reduction	Last 100 MW
0	5	0.0		
100	5	69.1	69%	69.1
200	5	137.6	69%	68.5
300	5	204.4	68%	66.8
400	5	268.4	67%	64.1
500	5	324.8	65%	56.4
600	5	361.8	60%	37.0
700	5	395.4	56%	33.6
800	5	428.2	54%	32.8
900	5	447.1	50%	18.9
1000	5	461.6	46%	14.5

The results of analyzing the solar impact over the remaining days available in the summer season are shown in Table 7 below.

Table 7

Average Impact of Solar Capacity On Most Peak Summer Days				
Solar Capacity	Nbr Days	Peak Reduction (MW)	% Reduction	Last 100 MW
0	179	0.0		
100	179	53.9	54%	53.9
200	179	102.5	51%	48.5
300	179	144.4	48%	42.0
400	179	177.1	44%	32.7
500	179	201.2	40%	24.1
600	179	219.6	37%	18.4
700	179	233.7	33%	14.1
800	179	244.5	31%	10.8
900	179	253.4	28%	8.9
1000	179	261.0	26%	7.6

Having 1,000 MW of solar capacity on the system yields an average reduction in peak demand of 26% or 261 MW. On an incremental basis, the impact of the last 100 MW of solar is 7.6 MW on average. The conclusion is that the last 100 MW of capacity will provide about 7.6

MW of system capacity relief for most of the summer season, i.e., during the months of May through October, plus an additional 6.9 MW (=14.9-7.6 MW) on the summer peak day.

ADDENDUM

Introduction:

The purpose of this addendum is to present a preliminary analysis of a more recent composite solar profile. This new composite profile used 21 solar farms with a full year of data for the period June 1, 2018 through May 31, 2019. The profiles from these facilities were added together and scaled to create an updated composite profile. This new composite solar profile was used to validate the findings contained in the body of this report which were based a composite profile created from 7 solar farms.

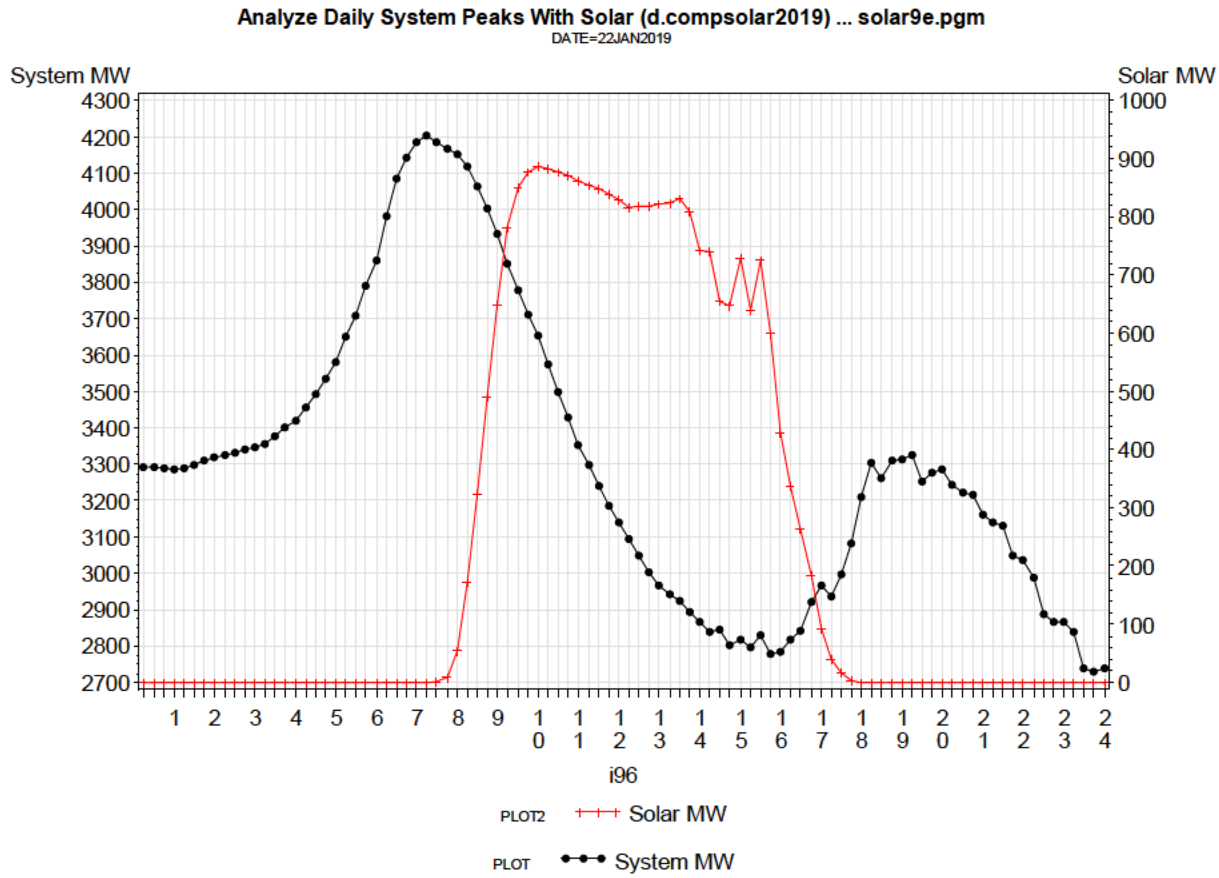
Preliminary Results:

The primary conclusion of the study, i.e., that solar power does not provide any capacity support to daily peaks in winter, is validated. Table 8 below is an update of Table 4 in the report. It shows that the latest winter peak occurred on January 22, 2019 at 7:15 am before solar is generating.

Table 8

Winter Peak Days on DESC's System		
Day of Peak	Peak MW	Time of Occurrence
January 07, 2014	4,717	7:30 a.m.
February 20, 2015	5,035	7:00 a.m.
January 19, 2016	4,451	7:00 a.m.
January 09, 2017	4,493	7:15 a.m.
January 05, 2018	4,776	8:00 a.m.
January 22, 2019	4,203	7:15 a.m.

The following graph shows the system load profile and the solar profile on the winter peak day. As the solar output is ramping up, the system load has already peaked and is beginning to decline as the sun warms the air and alleviates the heating load on the system.



The following chart shows how the winter system load profile net of solar changes as more solar is added to the system.

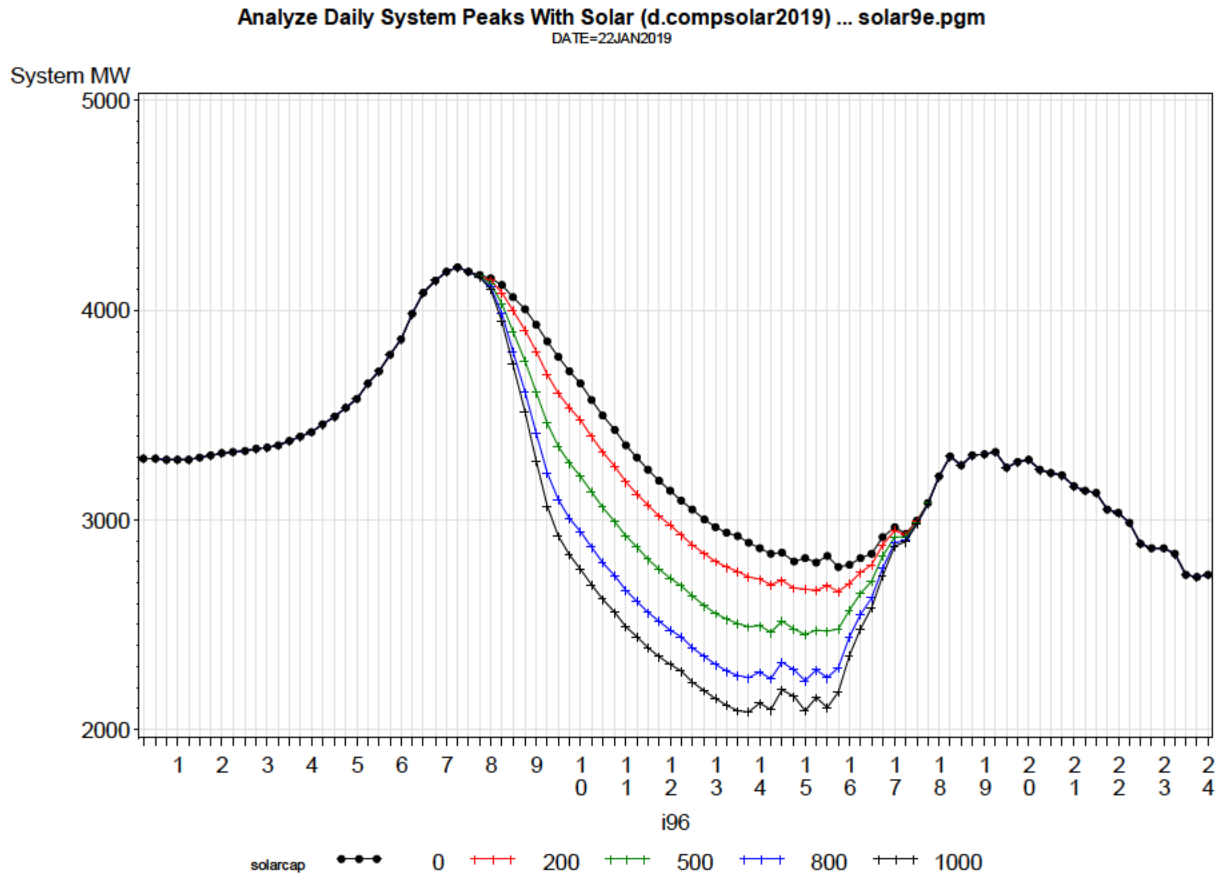
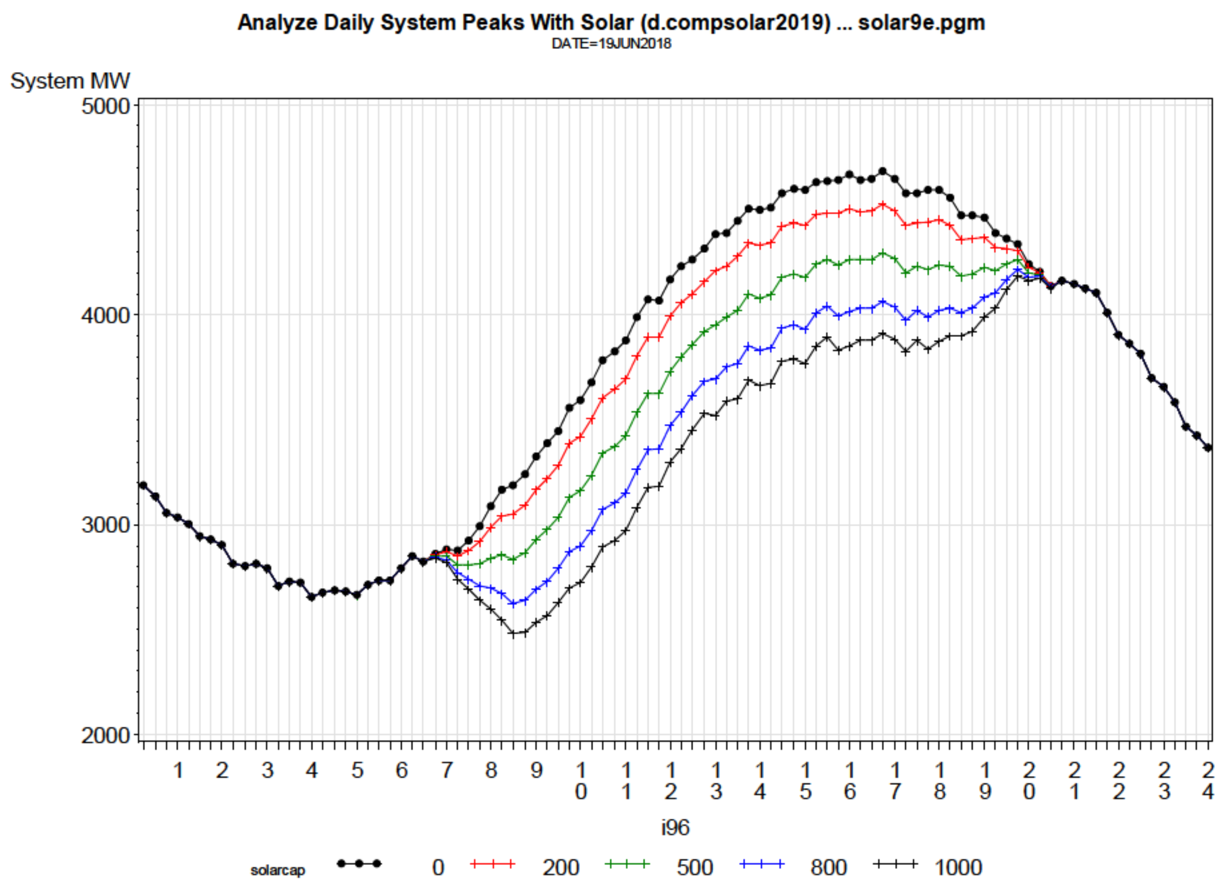


Table 9 is the update of Table 3 in the report. It shows again that there are many non-summer days where solar has no effect on the system peak load. The table does indicate that solar has an impact in summer, but also shows that the impact decreases with each incremental additional 100 MW of solar.

Table 9

Number of Days By Month When a 100 MW Increment in Solar Has Zero Impact on the Peak Demand										
	Amount of Solar Capacity on the System After the 100 MW Increment									
Month	100	200	300	400	500	600	700	800	900	1000
1	22	22	22	22	22	22	22	22	23	23
2	19	19	20	20	21	21	21	21	21	21
3	19	19	20	21	22	22	22	22	22	22
4	10	12	17	20	21	24	24	25	25	26
5	0	1	2	2	3	7	9	9	10	10
6	0	0	0	0	0	0	0	1	2	2
7	0	0	0	0	0	0	0	0	1	1
8	0	0	0	0	0	0	3	3	3	3
9	2	2	2	2	2	4	5	6	6	9
10	11	11	13	17	18	19	25	25	26	26
11	23	24	25	26	26	26	26	26	26	26
12	21	22	22	22	22	22	22	22	23	23
Total	127	132	143	152	157	167	179	182	188	192

The following chart shows the impact of solar on the 2018 summer peak day.



At some point after 500 MW of solar is added to the system, the peak load of the net system profile is shifted to around 8 pm and additional solar has no more effect.

Table 10 below provides the update to Table 6 in the report which shows the impact on summer peak days of various amounts of solar capacity. On the highest peak days of summer, 1000 MW of solar can be expected to generate about 47.8% of their nameplate capacity. This is a little higher than the 46% shown in Table 6.

Table 10

Average Impact of Solar Capacity On 5 Highest Peak Summer Days				
Solar Capacity	Nbr Days	Peak Reduction MW	% Reduction	Last 100 MW
0	5	0.0		
100	5	69.6	69.6	69.6
200	5	136.9	68.5	67.3
300	5	203.5	67.8	66.6
400	5	264.6	66.2	61.1
500	5	320.1	64.0	55.5
600	5	366.5	61.1	46.4
700	5	405.7	58.0	39.3
800	5	433.4	54.2	27.7
900	5	455.6	50.6	22.2
1000	5	477.8	47.8	22.2

Table 11 is the update for Table 7 in the report. It shows on most summer days that 1000 MW of solar will provide about 27.1% of its nameplate capacity.

Table 11

Average Impact of Solar Capacity On Most Peak Summer Days				
Solar Capacity	Nbr Days	Peak Reduction MWs	% Reduction	Last 100 MWs
0	179	0.0		
100	179	49.2	49.2	49.2
200	179	95.0	47.5	45.8
300	179	136.9	45.6	41.9
400	179	172.6	43.1	35.7
500	179	202.1	40.4	29.6
600	179	224.1	37.3	22.0
700	179	240.5	34.4	16.5
800	179	252.9	31.6	12.4
900	179	262.9	29.2	10.0
1000	179	270.6	27.1	7.7

The Peak Demand Forecast

Introduction

The peak demand forecasted growth is determined by the customer and sales forecast using the load characteristics of the different customer classes developed as part of the Company's Load Research Program. This report presents those load characteristics and the resulting peak demand forecast. The methodology for forecasting customers and sales involves many statistical and econometric models, a discussion of which is beyond the scope of this report. However, several comparisons of forecasted to historical growth in customers and sales are included to demonstrate the reasonableness of the forecast.

Table 1 below shows the forecast of the total internal demand, also known as the gross peak demand, for summer and winter. It also shows the projected net internal demand, also known as the firm peak demand, which requires supply resources to serve. The difference between these two demand concepts is the level of demand response currently available to the Company, most of which is comprised of interruptible customer load.

Table 1

	_Total Internal Demand__		_Net Internal Demand__		_Demand Response__	
wyr	Summer	Winter	Summer	Winter	Summer	Winter
2019	4,883	4,964	4,639	4,749	-244	-215
2020	4,933	5,008	4,688	4,792	-245	-216
2021	4,979	5,039	4,733	4,822	-246	-217
2022	5,019	5,078	4,772	4,860	-247	-218
2023	5,058	5,100	4,810	4,882	-248	-218
2024	5,084	5,140	4,835	4,921	-249	-219
2025	5,124	5,183	4,874	4,963	-250	-220
2026	5,170	5,228	4,919	5,007	-251	-221
2027	5,213	5,268	4,961	5,046	-252	-222
2028	5,257	5,308	5,003	5,085	-254	-223
2029	5,297	5,348	5,042	5,124	-255	-224
2030	5,340	5,391	5,084	5,166	-256	-225
2031	5,382	5,434	5,125	5,208	-257	-226
2032	5,426	5,475	5,168	5,248	-258	-227
2033	5,467	5,518	5,208	5,290	-259	-228
2034	5,510	5,558	5,250	5,329	-260	-229
2035	5,553	5,598	5,292	5,368	-261	-230
2036	5,596	5,638	5,334	5,407	-262	-231
2037	5,639	5,680	5,375	5,448	-264	-232

The projected growth rates of both the total and net internal demands over the period 2019-2037 is about 0.8%. The winter peak demands are higher than summer in both cases. For the total internal demand, the difference is 81 MW in 2019 and decreases to 41 MW by 2037. For the net internal demand, the difference is 110 MW in 2019 and 73 MW in 2037. It is important to keep in mind that the Company's resource plan calls for an increase in winter demand response which will lower the net internal demand in winter and may cause the net internal demand in summer to be larger than in winter. It is also worth noting that the above demands are not reported on a calendar basis. By utility convention, the winter season is thought to follow the summer season. Thus, the winter demands reflect an additional six months of system growth over summer.

Customer Class Characteristics

Except for the recent past, the Company's summer peak demands have always been larger than the winter seasonal peak demands. By examining the forecast methodology and how the customer load characteristics are used, it will be evident why the winter demands may dominate in the future. The following Table 2 contains the components used to derive the peak demand forecasts. The residential and commercial classes, i.e., 10.0 and 20.0, are projected using the number of customers in the forecast while the other classes are projected using GWH sales. The adjustments labeled Res.Adj and Com.Adj will be explained later. The entry labeled Ind.Adj or class=30.2 represents expansions planned by certain large customers which have been communicated to our customer representatives.

Table 2 – Calendar Based Information

			Energy Forecast		Summer Peak			Winter Peak	
yr	class	desc	Customer	GWH Sales	kW Per	Factor	Peak Demand	kW Per	Peak Demand
2019	10.0	Res	634,054	.	3.310	1.0098	2,119	3.973	2,519
	10.2	Res.Adj	.	.	.	.	-25	.	-22
	20.0	Com	97,221	.	15.887	1.0098	1,560	13.856	1,347
	20.2	Com.Adj	.	.	.	.	-3	.	-3
	30.0	Ind	.	5908.3	1.047	1.0098	713	0.904	610
	30.1	Ind.DR	.	.	.	.	210	.	178
	30.2	Ind.Adj	.	.	.	.	8	.	-7
	60.0	PSL	.	156.8	0.129	1.0098	2	0.157	3
	70.0	OPA	.	519.6	1.485	1.0098	89	1.232	73
	92.0	Muni	.	900.8	1.725	1.0098	179	1.722	177
	98.1	CoUse	.	.	.	.	31	.	32
	98.5	DR	.	.	.	.	-244	.	-214
2019			.	.	.	.	4,639	.	4,693
2020	10.0	Res	643,719	.	3.310	1.0098	2,152	3.973	2,558
	10.2	Res.Adj	.	.	.	.	-29	.	-32
	20.0	Com	98,116	.	15.887	1.0098	1,574	13.856	1,359
	20.2	Com.Adj	.	.	.	.	-3	.	-3
	30.0	Ind	.	5986.2	1.047	1.0098	723	0.904	618
	30.1	Ind.DR	.	.	.	.	211	.	179
	30.2	Ind.Adj	.	.	.	.	3	.	0
	60.0	PSL	.	157.0	0.129	1.0098	2	0.157	3
	70.0	OPA	.	519.5	1.485	1.0098	89	1.232	73
	92.0	Muni	.	901.2	1.725	1.0098	179	1.722	177
	98.1	CoUse	.	.	.	.	32	.	32
	98.5	DR	.	.	.	.	-245	.	-215
2020			.	.	.	.	4,688	.	4,749

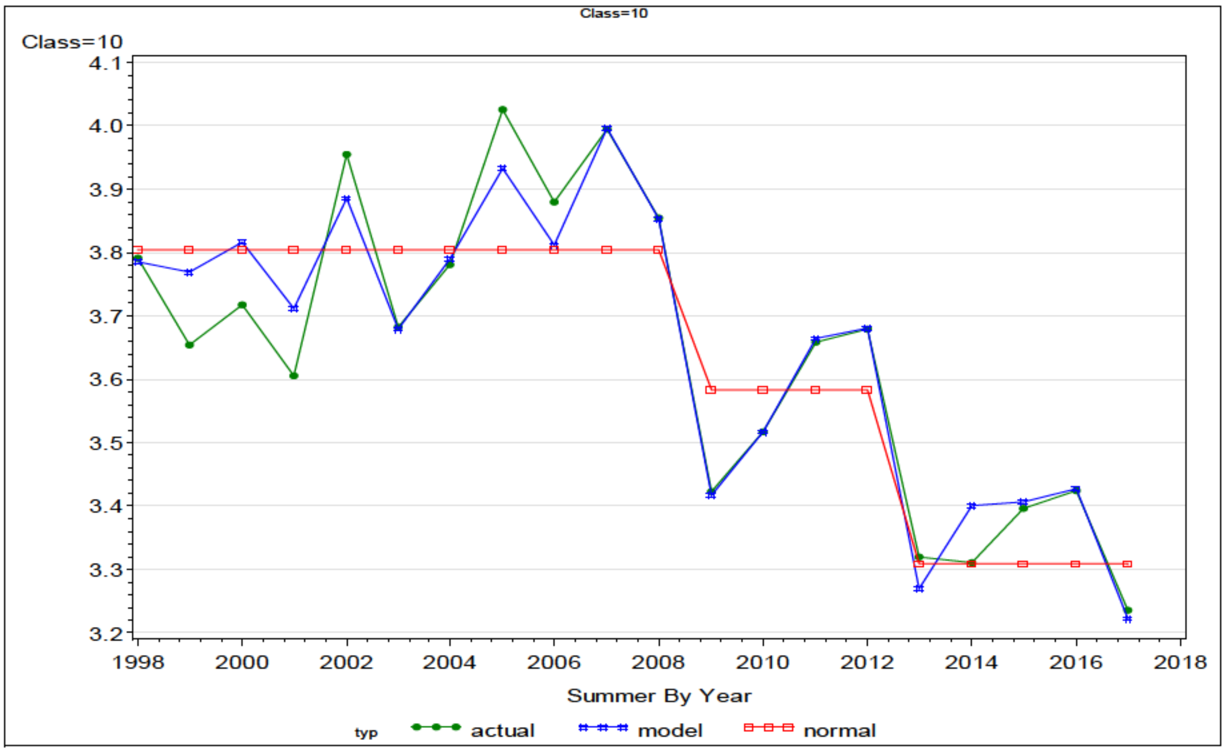
Table 1 shows that the summer net internal demand for 2019 is expected to be 4,639 MW which is shown in Table 2 as the sum of several customer components in the column labeled "Peak Demand." The first number in that column is the residential contribution to this total, labeled as class 10.0, and is equal to 2,119 MW. The formula for calculating this result is:

Peak Demand = Number of Customers * kW per customer * factor / 1000
= 634,054 * 3.310 * 1.0098 / 1000
= 2,119 MW

The number of residential customers, 634,054, is the average number for 2019 projected in the customer and sales forecast. The load characteristic of 3.310 kW per customer is the projected contribution to the four-hour (2-6 p.m.) summer system peak demand for the average residential customer. The "factor" is the average ratio of the one-hour summer peak demand to the four-hour average. Because the summer peak demand typically occurs in one of these four hours and the residential and commercial loads vary significantly by hour, the Company has used the four-hour period to conduct cost of service allocation studies for many years. The four-hour band is also used to project a more robust summer peak demand which must then be adjusted to the one-hour level, approximately a one percent adjustment.

The following chart shows the derivation of the kW per customer contribution to the summer peak demand for the average residential customer.

Chart 1



The chart shows the actual kW per customer going back to 1998 along with a regression model estimate and then a straight-line average based on normal weather. The regression model allows for this average to decrease over time as shown in the graph. The latest average is about 3.310 kW per customer. The average before the Great Recession[1] of 2008 was about 3.804, a 13% decrease.

The development of the winter peak demand forecast for 2019 is similar. As shown in Table 1, the winter net internal demand forecast for 2019 is 4,749 MW. Since the winter season follows the summer season, the components of the 2019 winter forecast must be taken from 2020 of Table 2 which reflects a calendar year. In Table 2 the peak demand of 4,749 MW is shown as the sum of several components and one of those components, labeled class 10.0, is the residential contribution of 2,558 MW. The formula for calculating this result is:

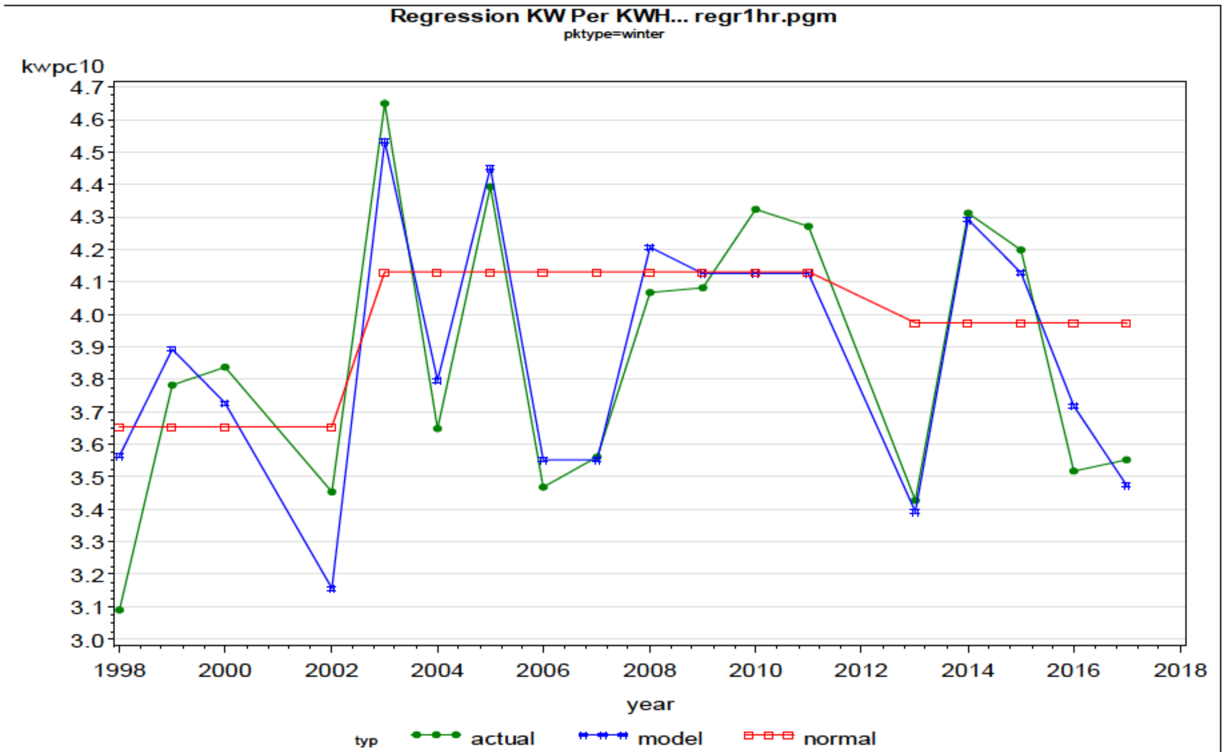
Peak Demand = Number of Customers * kW per customer / 1000
= 643,719 * 3.973 / 1000

[1] The National Bureau of Economic Research ("NBER") sets the dates of the Great Recession as beginning in December 2007 and ending in June 2009.

= 2,558 MW

The following chart shows the derivation of the kw per customer contribution to the winter peak demand for the average residential customer.

Chart 2



The current estimate of kW per customer of 3.973 reflects a small decrease from a previous period which reaches back to the pre-great recession years. The decrease from 4.132 kW per customer represents only a 3.8% decrease. It is worth noting that the largest kW per customer estimated in the Load Research Program was 4.649 kW per customer occurring in 2003. If circumstances, such as weather, resulted in the 643,719 residential customers increasing their demand from 3.973 to this maximum value of 4.649, it would mean an increase of 435 MW to their peak contribution, i.e. 643,719*(4.649-3.973).

The development of the commercial demand forecasts is identical to residential since it too relies on the number of customers. In winter then, the normal weather estimate of kW per customer contribution to peak is 13.856 and with a customer forecast for 2020 of 98,116 customers, the estimate of commercial class peak contribution in 2019 is 1,359 MW (=98,116*13.856). Remember the 2019 winter season follows the 2019 summer season. The actual kW per customer contribution to the winter peak in 2003 was 15.391. So, if weather like 2003 occurs during the 2019/2020 winter season, the commercial contribution to peak could increase by 151 MW (=98,116*(15.391-13.856)). Combining the commercial and residential demand related weather risk yields a combined weather risk of 586 MW. The following Table 3 summarizes the results.

Table 3

2019 Combined Residential and Commercial Demand-side Winter Weather Risk				
	Customers	2003 kW per Customer	Normal kW per Customer	Risk Estimate
Residential	643,719	4.649	3.973	435 MW
Commercial	98,116	15.391	13.856	151 MW

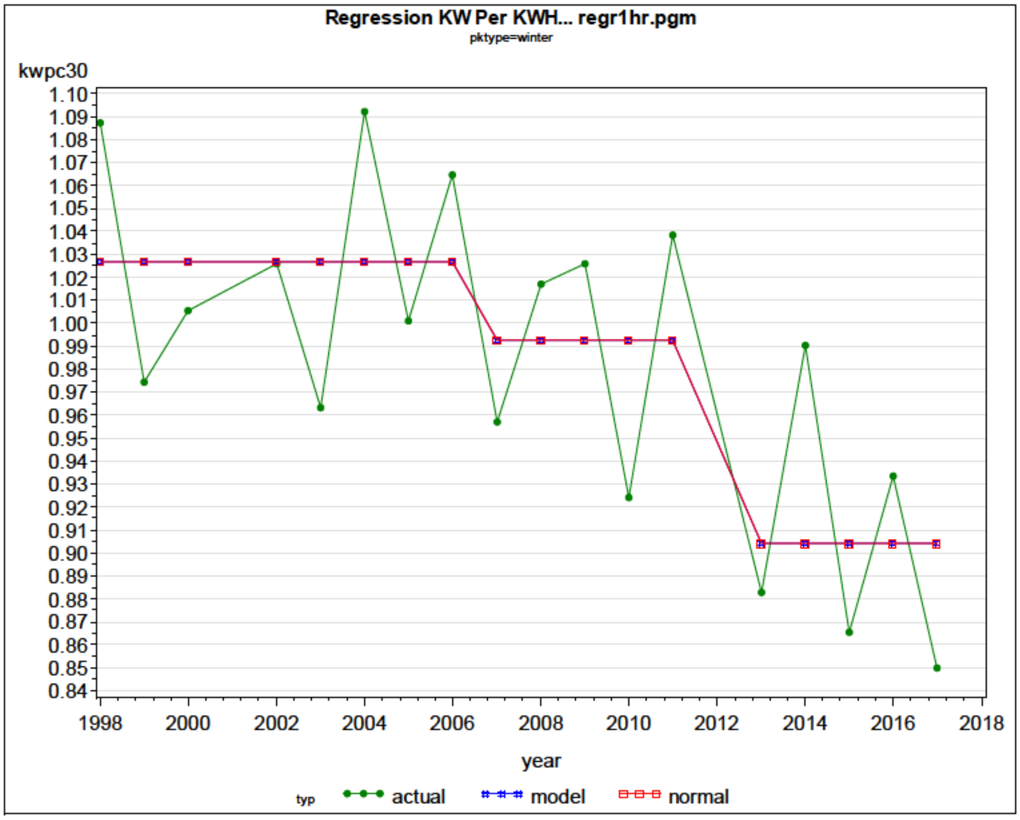
The industrial demand forecast relies on GWH sales, so it may be useful to review its formula. As already noted, the winter net internal demand for 2019 shown in Table 1 is 4,749 MW and this corresponds to the same number in Table 2 shown for 2020 as the sum of several components. The industrial contribution to this total, 618 MW, appears in the middle of the list of components and is labeled as class = "30.0 Ind." The formula for calculating the industrial demand forecast is:

Peak Demand = (GWH Sales / number of hours) * kW per Average kWh
= (5,986.2 / 8.760) * 0.904
= 618 MW

The 618 MW represents the firm part of industrial load. The non-firm portion or interruptible part is 179 MW and is shown in Table 2 with the label "Ind.DR" or class=30.1. The interruptible load is estimated using load research interval data for those customers participating in the Company's interruptible program. The total industrial winter peak demand, firm plus interruptible, is 797 MW.

The following chart shows the derivation of the kw per customer contribution to the winter peak demand for the average residential customer.

Chart 3



Since the industrial load does not vary with weather, the model and normal estimates are the same in the chart.

Calculations like those above were made for each class of customer, each season and each year to produce the forecast. The appendix contains charts for each customer class and season as well as a table like Table 2 for the years 2020, 2025, and 2030.

Detail Components of Peak Demand Forecast

The following Table 4 shows all the components that comprise the summer peak demand forecast. The rows labeled 10.5, 10.6, 10.7, 10.8 and 10.9 comprise the amount of load grouped under the label "Res.Adj" earlier in Table 2. The rows labeled 20.6 and 20.7 comprise "Com.Adj."

Table 4 - SUMMER PEAK DEMAND FORECAST

class	desc	iord	_2019	_2020	_2021	_2022	_2023	_2024	_2025	_2026
10.0	Residential	1	2,119	2,152	2,186	2,216	2,244	2,271	2,299	2,328
10.5	Res SEER	5	-9	-10	-11	-13	-15	-33	-37	-41
10.6	Res Eff Lites	6	0	0	0	0	0	0	0	0
10.7	Res SCE&G EE	7	0	0	-6	-12	-18	-24	-30	-36
10.8	Res Water Heater Eff.	8	0	0	-1	-1	-1	-1	-1	-1
10.9	Res NEM Solar PV	9	-16	-19	-20	-21	-21	-21	-21	-21
20.0	Commercial	10	1,560	1,574	1,596	1,616	1,635	1,655	1,674	1,694
20.5	Com Standby Gen	11	-11	-11	-11	-11	-11	-11	-11	-11
20.6	Com Eff Lites	12	-3	-3	-10	-19	-27	-32	-36	-39
20.7	Com SCE&G EE	13	0	0	-1	-2	-4	-5	-6	-7
30.0	Industrial	14	931	937	942	949	956	962	968	976
60.0	PSL	15	2	2	2	2	2	2	2	3
70.0	OPA	16	89	89	90	91	93	94	95	96
80.0	Company Use	19	31	32	32	32	32	33	33	33
92.0	Municipals	17	179	179	180	181	182	183	184	185
97.0	Cooperatives	18	.	.	.	.	.	.	.	.
99.1	Standby Gen	20	-25	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	21	-208	-209	-210	-211	-212	-213	-214	-215
		=====	=====	=====	=====	=====	=====	=====	=====	=====
		222	4,639	4,688	4,733	4,772	4,810	4,835	4,874	4,919

class	desc	_2027	_2028	_2029	_2030	_2031	_2032	_2033	class
10.0	Residential	2,357	2,387	2,416	2,445	2,474	2,503	2,532	10.0
10.5	Res SEER	-45	-49	-54	-56	-57	-58	-59	10.5
10.6	Res Eff Lites	0	0	0	0	0	0	0	10.6
10.7	Res SCE&G EE	-43	-49	-56	-63	-70	-77	-84	10.7
10.8	Res Water Heater Eff.	-2	-2	-2	-2	-2	-2	-2	10.8
10.9	Res NEM Solar PV	-21	-21	-21	-21	-21	-22	-22	10.9
20.0	Commercial	1,713	1,733	1,753	1,772	1,792	1,811	1,830	20.0
20.5	Com Standby Gen	-11	-11	-11	-11	-11	-11	-11	20.5
20.6	Com Eff Lites	-39	-45	-51	-57	-63	-69	-76	20.6
20.7	Com SCE&G EE	-9	-10	-11	-12	-14	-15	-16	20.7
30.0	Industrial	983	991	999	1,007	1,014	1,022	1,029	30.0
60.0	PSL	3	3	3	3	3	3	3	60.0
70.0	OPA	97	98	99	101	102	103	104	70.0
80.0	Company Use	33	34	34	34	34	35	35	80.0
92.0	Municipals	186	187	188	189	190	192	193	92.0
97.0	Cooperatives	.	.	.	.	.	.	.	97.0
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25	99.1
99.2	Interruptible Loads	-216	-218	-219	-220	-221	-222	-223	99.2
		=====	=====	=====	=====	=====	=====	=====	=====
		4,961	5,003	5,042	5,084	5,125	5,168	5,208	772.6

The following Table 5 has a description of each component in the forecast.

Table 5

Category		Description
10.0	Residential	Residential Base Load
10.5	Res SEER	Adjustment for Improved SEER Rating
10.6	Res Eff Lites	Adjusment for More Efficient Lighting
10.7	Res SCE&G EE	Adjustment for Incremental Impact of SCE&G EE Programs
10.8	Res Water Heater Eff.	Adjustment for Improved Water Heater Efficiency
10.9	Res NEM Solar PV	Adjustment for Incremental NEM Customers
20.0	Commercial	Commercial Base Load
20.5	Com Standby Gen	Retail Standby Generation
20.6	Com Eff Lites	Adjusment for More Efficient Lighting
20.7	Com SCE&G EE	Adjustment for Incremental Impact of SCE&G EE Programs
30.0	Industrial	Industrial Base Load
60.0	PSL	Public Street Lighting
70.0	OPA	Other Public Authorities
80.0	Company Use	Company Use
92.0	Municipals	Municipalities
97.0	Cooperatives	Cooperatives
99.1	Standby Gen	Wholesale Standby Generation
99.2	Interruptible Loads	Retail Interruptible Load

The following Table 6 shows all the components that comprise the winter peak demand forecast.

Table 6 - WINTER PEAK DEMAND FORECAST

class	desc	iord	_2019	_2020	_2021	_2022	_2023	_2024	_2025	_2026
10.0	Residential	1	2,558	2,599	2,634	2,667	2,700	2,733	2,767	2,802
10.5	Res SEER	5	-10	-11	-13	-15	-33	-37	-41	-45
10.6	Res Eff Lites	6	-20	-30	-40	-42	-44	-47	-49	-52
10.7	Res SCE&G EE	7	0	-6	-12	-18	-24	-30	-36	-42
10.8	Res Water Heater Eff.	8	-2	-3	-4	-4	-5	-5	-6	-6
10.9	Res NEM Solar PV	9	0	0	0	0	0	0	0	0
20.0	Commercial	10	1,359	1,379	1,396	1,412	1,429	1,446	1,463	1,479
20.5	Com Standby Gen	11	-11	-11	-11	-11	-11	-11	-11	-11
20.6	Com Eff Lites	12	-3	-10	-19	-26	-32	-36	-38	-39
20.7	Com SCE&G EE	13	0	-1	-2	-4	-5	-6	-7	-8
30.0	Industrial	14	797	804	810	816	820	826	832	838
60.0	PSL	15	3	3	3	3	3	3	3	3
70.0	OPA	16	73	74	75	76	77	78	79	80
80.0	Company Use	19	32	32	32	33	33	33	33	34
92.0	Municipals	17	177	178	179	180	181	182	183	184
97.0	Cooperatives	18	.	.	.	.	.	.	.	.
99.1	Standby Gen	20	-25	-25	-25	-25	-25	-25	-25	-25
99.2	Interruptible Loads	21	-179	-180	-181	-182	-182	-183	-184	-185
		=====	=====	=====	=====	=====	=====	=====	=====	=====
		222	4,749	4,792	4,822	4,860	4,882	4,921	4,963	5,007

class	desc	_2027	_2028	_2029	_2030	_2031	_2032	_2033	class
10.0	Residential	2,837	2,873	2,906	2,941	2,976	3,010	3,045	10.0
10.5	Res SEER	-49	-53	-55	-56	-57	-58	-60	10.5
10.6	Res Eff Lites	-54	-57	-60	-62	-65	-68	-71	10.6
10.7	Res SCE&G EE	-49	-56	-62	-69	-76	-83	-90	10.7
10.8	Res Water Heater Eff.	-7	-8	-8	-8	-8	-8	-8	10.8
10.9	Res NEM Solar PV	0	0	0	0	0	0	0	10.9
20.0	Commercial	1,497	1,514	1,530	1,547	1,564	1,581	1,598	20.0
20.5	Com Standby Gen	-11	-11	-11	-11	-11	-11	-11	20.5
20.6	Com Eff Lites	-45	-51	-57	-63	-69	-75	-81	20.6
20.7	Com SCE&G EE	-10	-11	-12	-14	-15	-16	-17	20.7
30.0	Industrial	845	852	859	865	872	878	885	30.0
60.0	PSL	3	3	3	3	3	3	3	60.0
70.0	OPA	81	82	83	84	85	85	86	70.0
80.0	Company Use	34	34	34	35	35	35	36	80.0
92.0	Municipals	185	186	187	188	189	191	192	92.0
97.0	Cooperatives	.	.	.	.	.	.	.	97.0
99.1	Standby Gen	-25	-25	-25	-25	-25	-25	-25	99.1
99.2	Interruptible Loads	-186	-187	-188	-189	-190	-191	-192	99.2
		=====	=====	=====	=====	=====	=====	=====	=====
		5,046	5,085	5,124	5,166	5,208	5,248	5,290	772.6

Customer and Sales Growth Comparisons: History and Forecast

The following table shows the growth in customers and sales over the last five years and that projected over the next five years. The variable or header labeled “hisgr” is the compound average annual growth rate for the years 2013 through 2018 and the variable “forgr” is the growth rate for the period 2018 through 2023. For the residential class, the number of customers is the driver for growth in residential peak demand. The table shows that the projected growth over the next five years is only slightly lower than over the previous five years, i.e., 1.5% versus 1.4%. Similarly, for the commercial class of customers, the projected growth rate is only slightly lower than the historical rate, 1.2% versus 1.1%. While not affecting the peak demand forecast, the weather normalized average kWh per customer for both residential and commercial customers is expected to continue declining over the next five years but at a slower rate than in the last five years. Industrial GWH sales are expected to decrease over the next five years but this is mostly an accounting phenomenon which is explained after tables 7 and 8.

Table 7 – Customers and Weather Normalized Sales Over +/- 5 Years

CLASS=Residential

desc	CLASS	_2013	_2018	_2023	hisgr	forgr
Nbr Customers	Residential	580,407	624,849	671,268	1.5	1.4
kWh per Customer	Residential	13,407	12,701	12,177	-1.1	-0.8
Total GWH Sales	Residential	7,782	7,936	8,174	0.4	0.6

CLASS=Commercial

desc	CLASS	_2013	_2018	_2023	hisgr	forgr
Nbr Customers	Commercial	90,770	96,378	101,944	1.2	1.1
kWh per Customer	Commercial	80,287	74,435	73,385	-1.5	-0.3
Total GWH Sales	Commercial	7,288	7,174	7,481	-0.3	0.8

CLASS=Industrial

desc	CLASS	_2013	_2018	_2023	hisgr	forgr
Total GWH Sales	Industrial	6,005	6,321	6,143	1.0	-0.6

CLASS=All_Sales

desc	CLASS	_2013	_2018	_2023	hisgr	forgr
Total GWH Sales	All_Sales	22,625	22,916	23,331	0.3	0.4

The following Table 8 contains similar information on a 15-year basis, which also reflects a similar result.

Table 8 – Customers and Weather Normalized Sales Over +/- 15 Years

CLASS=Residential

desc	CLASS	_2003	_2018	_2033	hisgr	forgr
Nbr Customers	Residential	481,380	624,849	757,596	1.8	1.3
kWh per Customer	Residential	14,876	12,701	12,251	-1.0	-0.2
Total GWH Sales	Residential	7,161	7,936	9,282	0.7	1.0

CLASS=Commercial

desc	CLASS	_2003	_2018	_2033	hisgr	forgr
Nbr Customers	Commercial	78,999	96,378	114,094	1.3	1.1
kWh per Customer	Commercial	84,798	74,435	69,800	-0.9	-0.4
Total GWH Sales	Commercial	6,699	7,174	7,964	0.5	0.7

CLASS=Industrial

desc	CLASS	_2003	_2018	_2033	hisgr	forgr
Total GWH Sales	Industrial	6,543	6,321	6,658	-0.2	0.3

CLASS=All_Sales

desc	CLASS	_2003	_2018	_2033	hisgr	forgr
Total GWH Sales	All_Sales	22,347	22,916	25,563	0.2	0.7

Regarding the projected growth, or lack thereof, of industrial sales, the generator in a large cogeneration facility has been acquired from DESC by the host manufacturing customer. Therefore, instead of the generator output being DESC's generation and all energy consumption by the host being recorded as DESC's industrial sales, the generator output will be consumed at the customer's site and only the residual energy needs of the host customer will be industrial sales from DESC. To obtain a better estimate of industrial growth on DESC's system, 500 GWHs can be added to the industrial sales level in the forecasted years. For example, the adjusted industrial growth rate for the years 2018 through 2023 is 1.0% instead of -0.6% as shown in the table and for the period 2018-2033, the adjusted growth is 0.8% instead of -0.2% as shown in the table.

APPENDIX

Figure A1: Containing Components of Demand Forecast in Future "Calendar" Years

			Energy Forecast		Summer Peak			Winter Peak	
yr	class	desc	Customer	GWH Sales	kW Per	Factor	Peak Demand	kW Per	Peak Demand
2020	10.0	Res	643,719	.	3.310	1.0098	2,152	3.973	2,558
	10.2	Res.Adj	.	.	.	.	-29	.	-32
	20.0	Com	98,116	.	15.887	1.0098	1,574	13.856	1,359
	20.2	Com.Adj	.	.	.	.	-3	.	-3
	30.0	Ind	.	5986.2	1.047	1.0098	723	0.904	618
	30.1	Ind.DR	.	.	.	.	211	.	179
	30.2	Ind.Adj	.	.	.	.	3	.	0
	60.0	PSL	.	157.0	0.129	1.0098	2	0.157	3
	70.0	OPA	.	519.5	1.485	1.0098	89	1.232	73
	92.0	Muni	.	901.2	1.725	1.0098	179	1.722	177
	98.1	CoUse	.	.	.	.	32	.	32
	98.5	DR	.	.	.	.	-245	.	-215
2020			.	.	.	.	4,688	.	4,749
2025	10.0	Res	687,796	.	3.310	1.0098	2,299	3.973	2,733
	10.2	Res.Adj	.	.	.	.	-89	.	-119
	20.0	Com	104,361	.	15.887	1.0098	1,674	13.856	1,446
	20.2	Com.Adj	.	.	.	.	-42	.	-42
	30.0	Ind	.	6230.8	1.047	1.0098	752	0.904	643
	30.1	Ind.DR	.	.	.	.	216	.	183
	60.0	PSL	.	167.3	0.129	1.0098	2	0.157	3
	70.0	OPA	.	554.3	1.485	1.0098	95	1.232	78
	92.0	Muni	.	924.5	1.725	1.0098	184	1.722	182
	98.1	CoUse	.	.	.	.	33	.	33
	98.5	DR	.	.	.	.	-250	.	-219
2025			.	.	.	.	4,874	.	4,921
2030	10.0	Res	731,487	.	3.310	1.0098	2,445	3.973	2,906
	10.2	Res.Adj	.	.	.	.	-142	.	-185
	20.0	Com	110,442	.	15.887	1.0098	1,772	13.856	1,530
	20.2	Com.Adj	.	.	.	.	-69	.	-69
	30.0	Ind	.	6499.4	1.047	1.0098	785	0.904	671
	30.1	Ind.DR	.	.	.	.	222	.	188
	60.0	PSL	.	177.8	0.129	1.0098	3	0.157	3
	70.0	OPA	.	587.4	1.485	1.0098	101	1.232	83
	92.0	Muni	.	951.9	1.725	1.0098	189	1.722	187
	98.1	CoUse	.	.	.	.	34	.	34
	98.5	DR	.	.	.	.	-256	.	-224
2030			.	.	.	.	5,084	.	5,124

Concerning Figures A2-A13

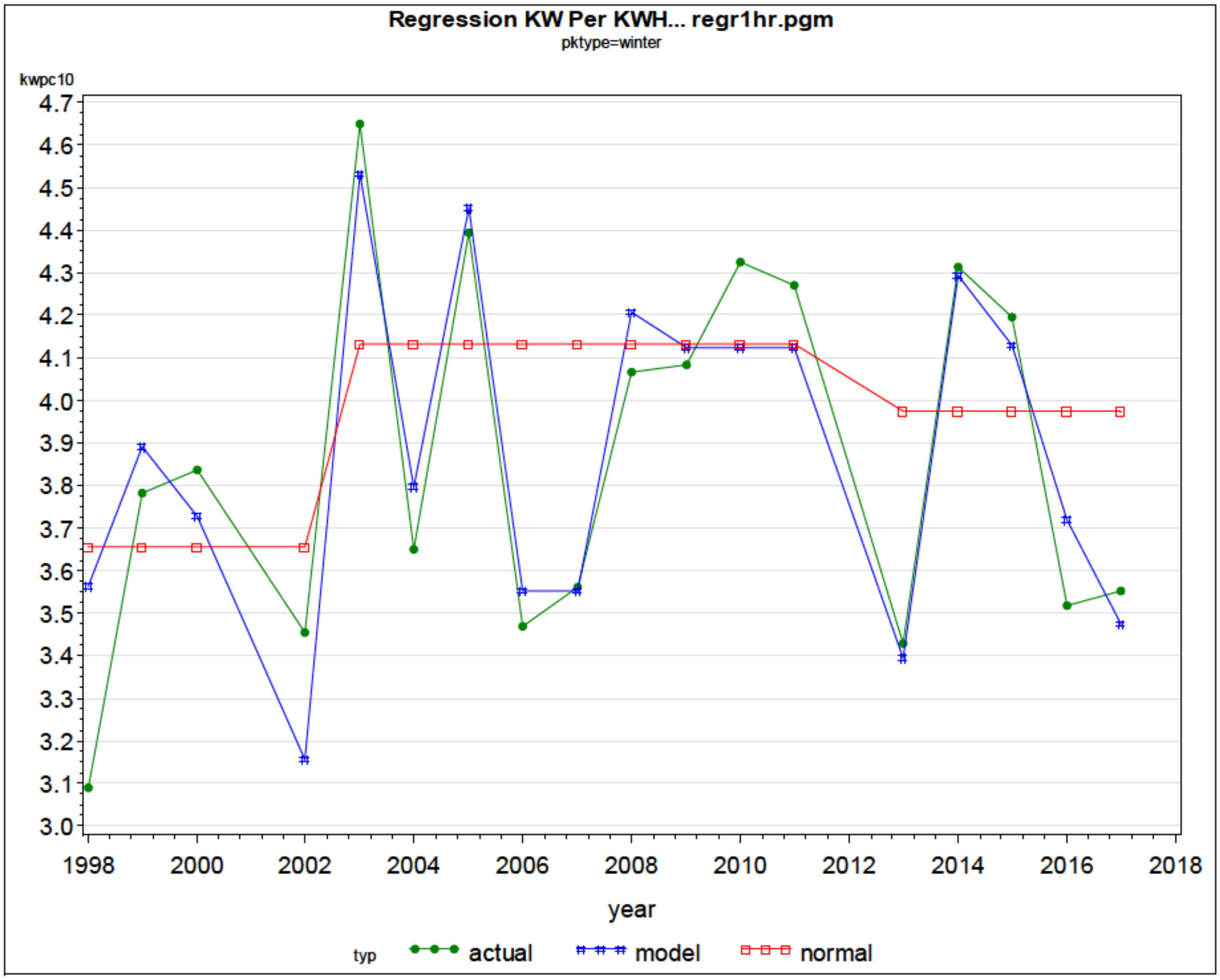
Figures A2-A13 show the results of an “Analysis of Variance” approach to the changes in kW per customer or kW per kWh for each of the classes of customer, i.e. an ANOVA model. When weather is a statistically significant factor in the variation of peak contribution, an “Analysis of Covariance” is used, i.e. an ANCOVA model. Figures A2-A7 show results for the winter and Figures A8-A13, for the summer. The customer classes are: residential, commercial, industrial, pubic street lighting, other public authorities, and municipalities.

The fixed effects variables are 0-1 dummy variables where the start and stop year, i.e. the years when the variable equals one, are indicated in the name of the variable. For example, in Figure A2 showing results for the residential class in winter, the variable “i03_11”, takes on the value 1 in the years 2003 through 2011 and 0 elsewhere.

The weather variables for the peak day used in the models are:

Mntmp=minimum daily temperature;
Hdh60 = heating degree hours base 60;
Cdh = cooling degree hours base 75; and
Maxtmp=maximum daily temperature.

Figure A2: Residential Winter kW per Customer Regression Equation

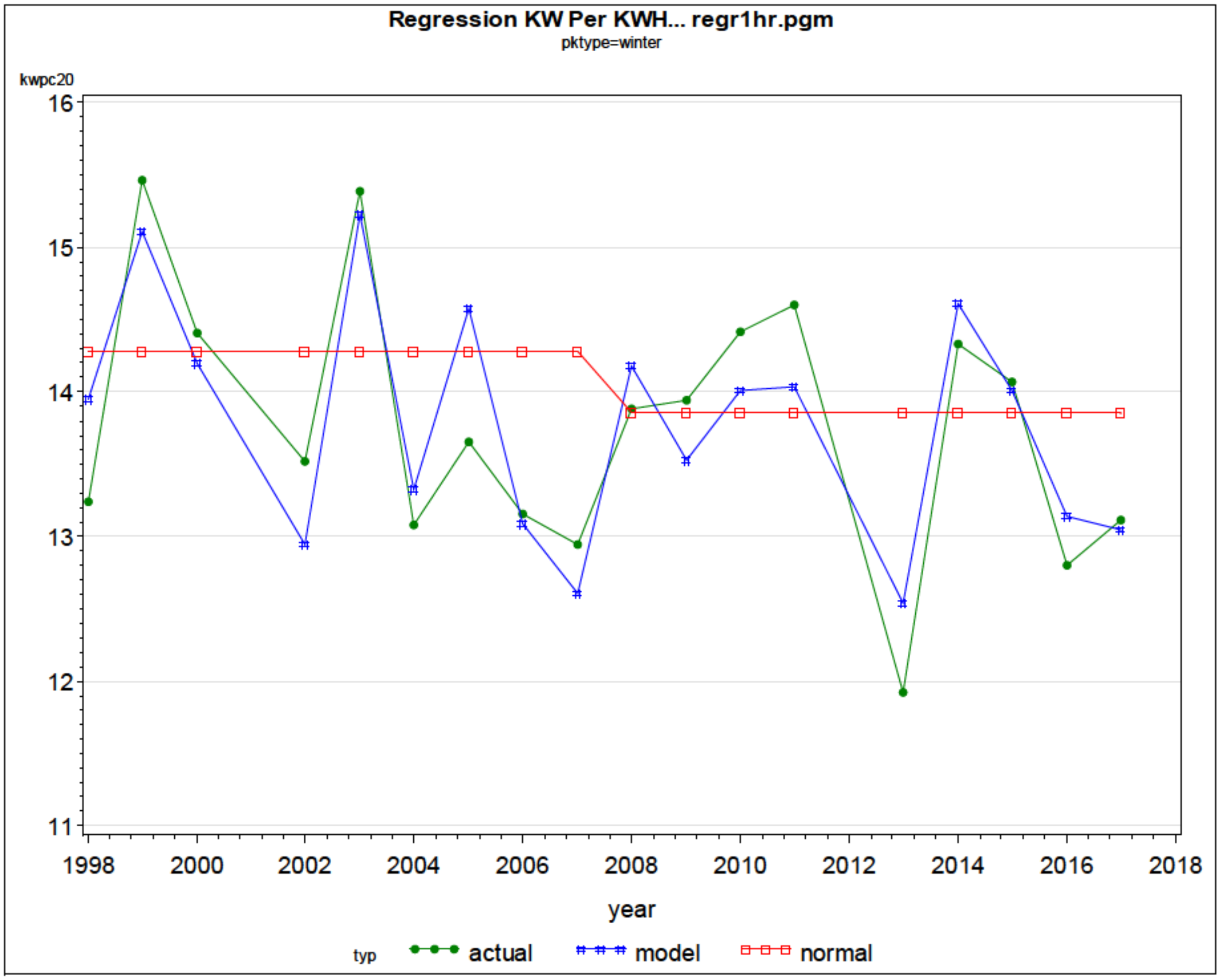


Root MSE	0.16765	R-Square	0.8600
Dependent Mean	3.89496	Adj R-Sq	0.8300
Coeff Var	4.30439		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	5.60029	0.23202	24.14	<.0001	0
i98_02	1	-0.31863	0.11965	-2.66	0.0185	1.36938
i03_11	1	0.15893	0.09417	1.69	0.1136	1.36462
mntmp	1	-0.08176	0.00998	-8.19	<.0001	1.02115

Figure A3: Commercial Winter kW per Customer Regression Equation

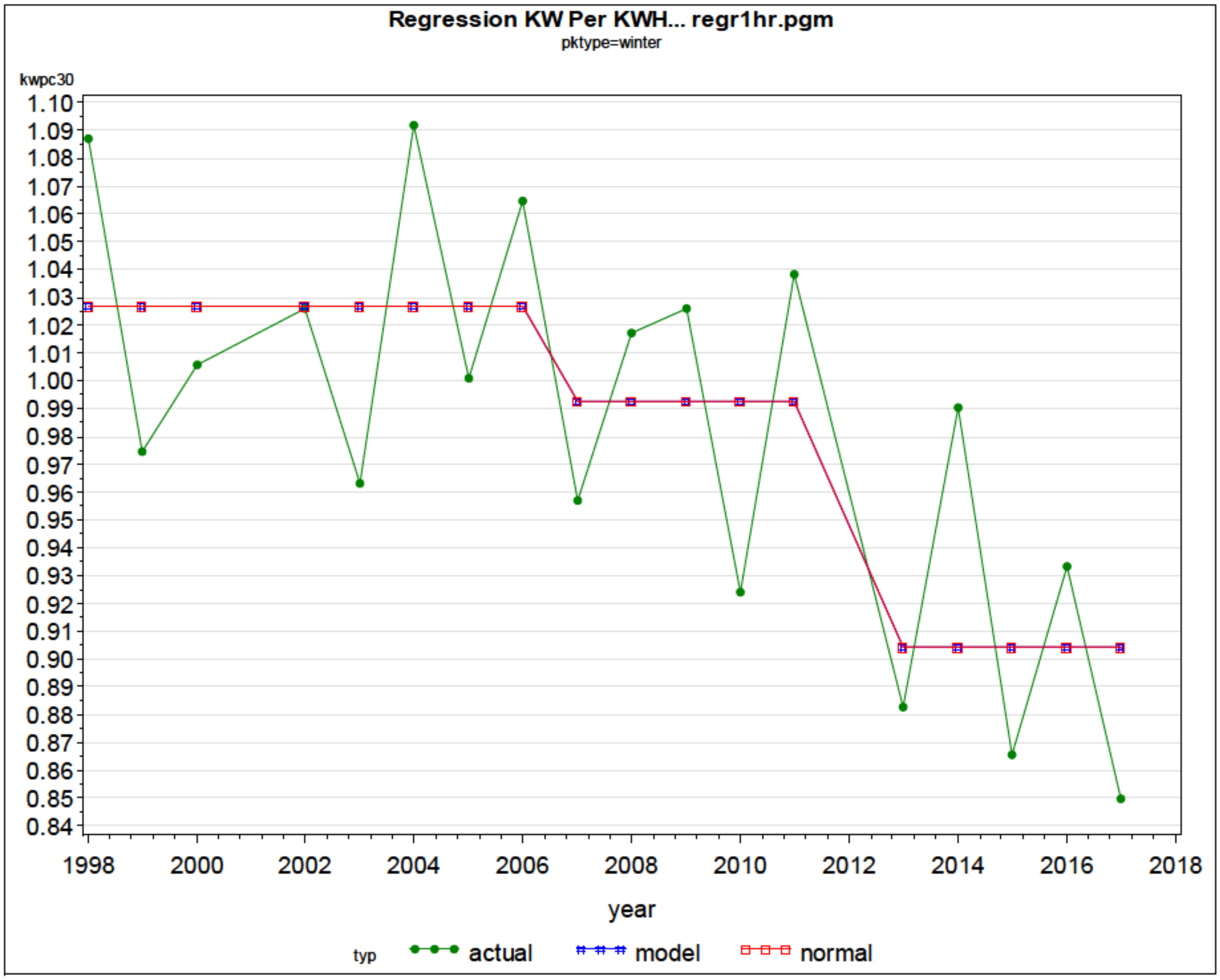


Root MSE	0.46576	R-Square	0.7694
Dependent Mean	13.77535	Adj R-Sq	0.7386
Coeff Var	3.38112		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.58985	1.02200	6.45	<.0001	0
i98_07	1	0.42590	0.22305	1.91	0.0755	1.02117
hdh60	1	0.02400	0.00342	7.02	<.0001	1.02117

Figure A4: Industrial Winter kW per kWh Regression Equation

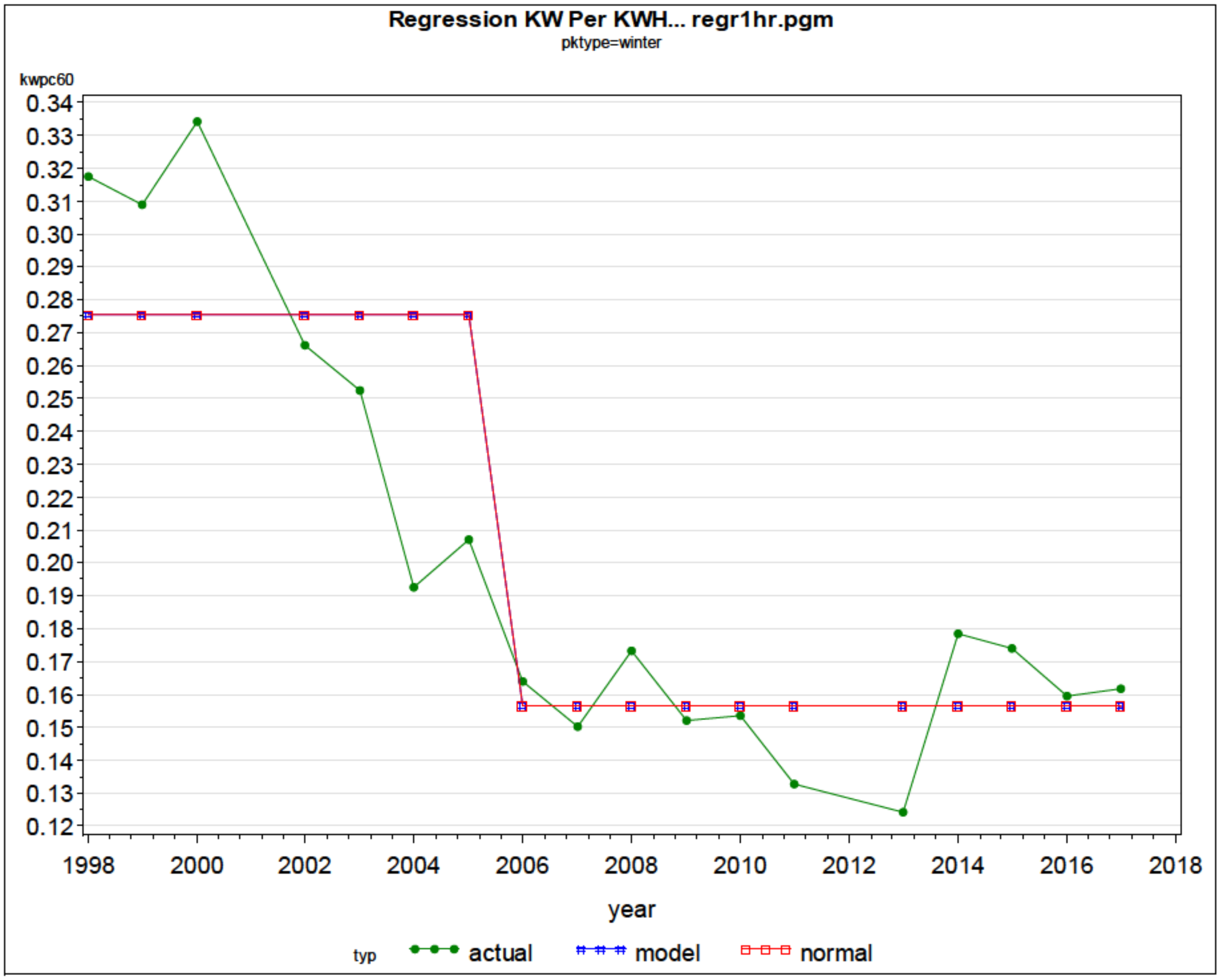


Root MSE	0.05172	R-Square	0.5383
Dependent Mean	0.98318	Adj R-Sq	0.4767
Coeff Var	5.26080		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.90408	0.02316	39.03	<.0001	0
i98_06	1	0.12263	0.02951	4.16	0.0008	1.44605
i07_11	1	0.08833	0.03274	2.70	0.0165	1.44605

Figure A5: Public Street Lighting Winter kW per kWh Regression Equation

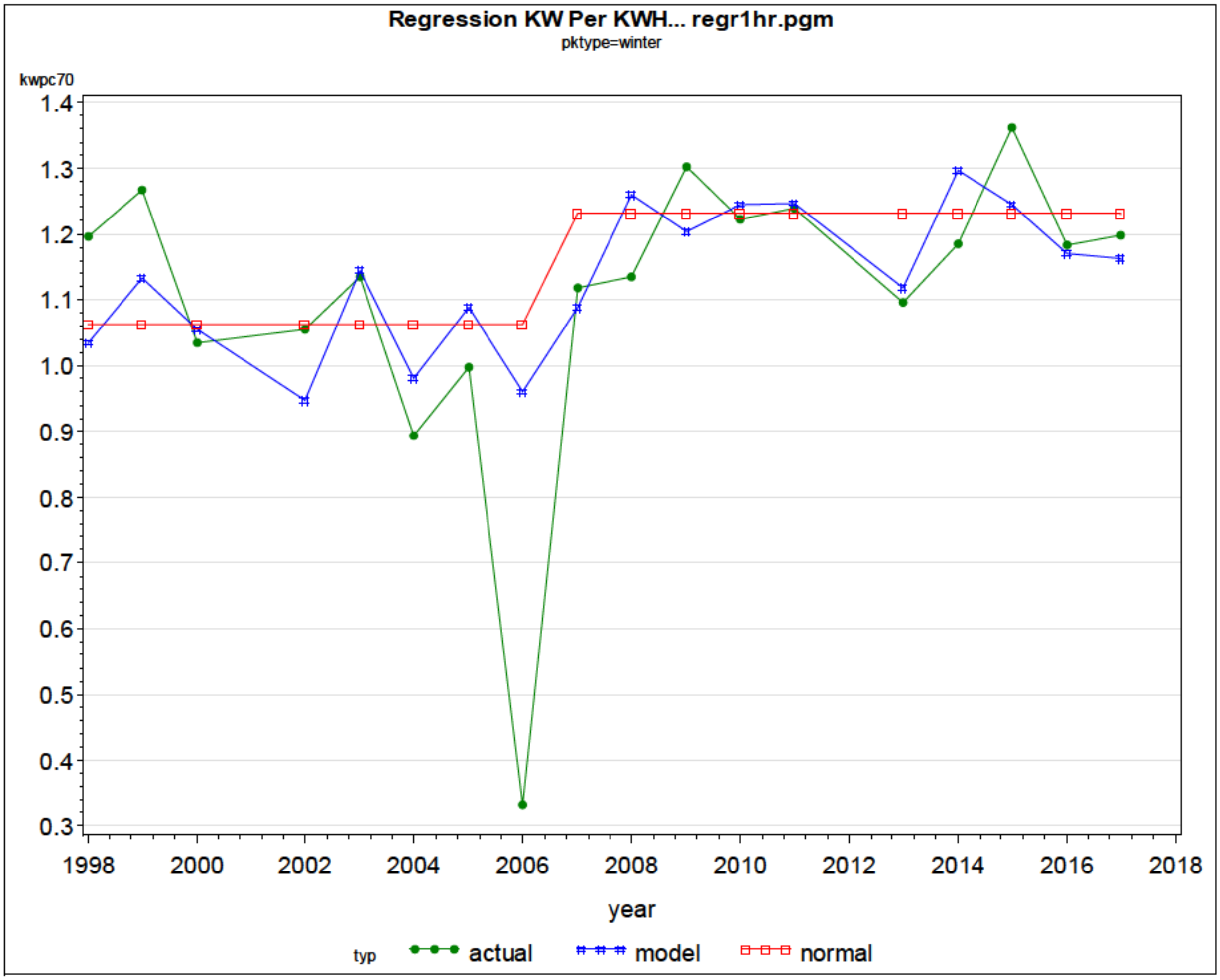


Root MSE	0.03107	R-Square	0.7780
Dependent Mean	0.19808	Adj R-Sq	0.7641
Coeff Var	15.68591		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.15665	0.00937	16.72	<.0001	0
i98_05	1	0.11875	0.01586	7.49	<.0001	1.00000

Figure A6: Other Public Authorities Winter kW per kWh Regression Equation

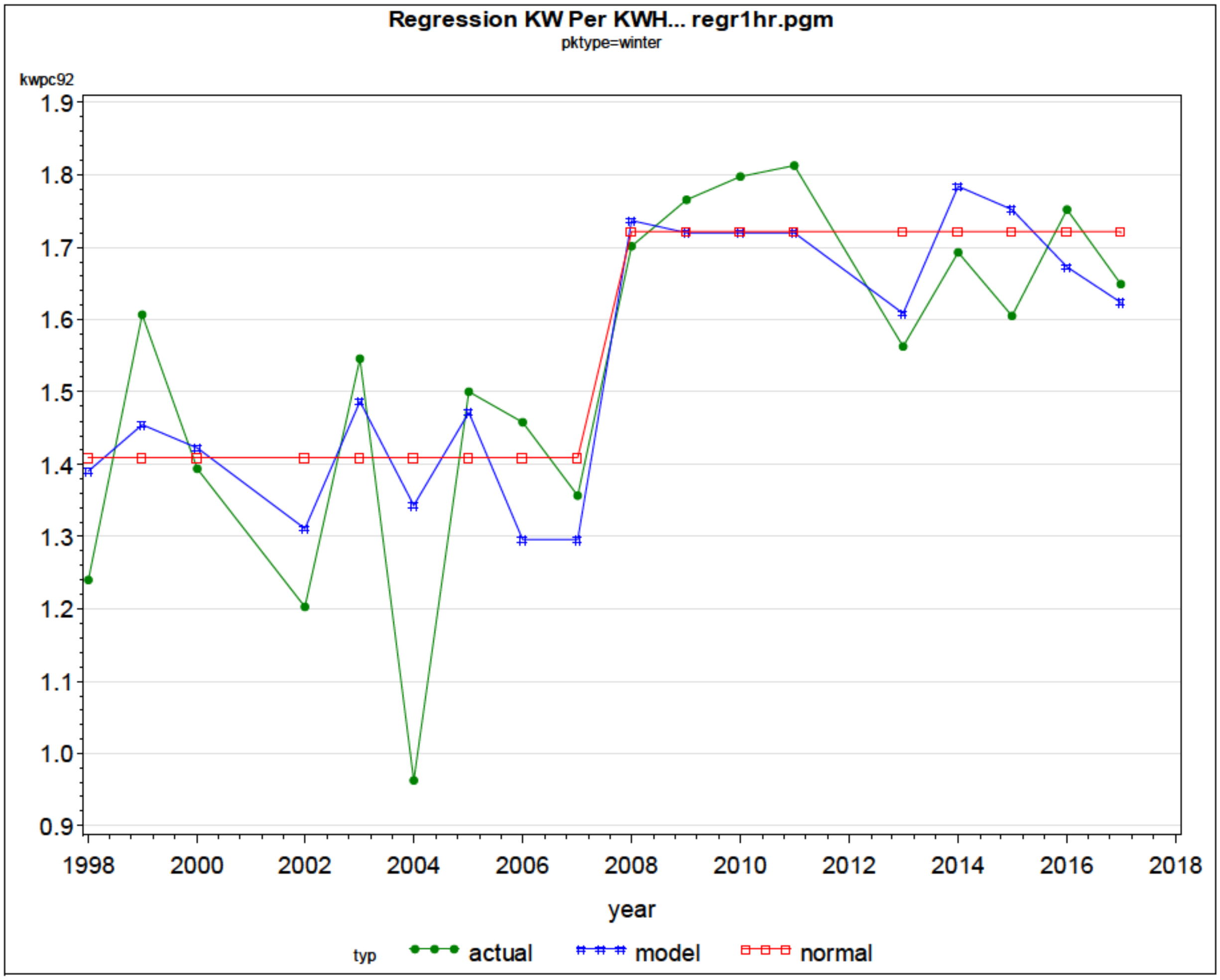


Root MSE	0.12947	R-Square	0.4117
Dependent Mean	1.13890	Adj R-Sq	0.3333
Coeff Var	11.36830		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.60597	0.28380	2.14	0.0496	0
i98_06	1	-0.17013	0.06345	-2.68	0.0171	1.01477
hdh60	1	0.00207	0.00097174	2.13	0.0502	1.01477

Figure A7: Municipal Winter kW per kWh Regression Equation



Root MSE	0.11997	R-Square	0.7024
Dependent Mean	1.55133	Adj R-Sq	0.6627
Coeff Var	7.73352		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.04098	0.15377	13.27	<.0001	0
i98_07	1	-0.31344	0.05747	-5.45	<.0001	1.00040
mntmp	1	-0.01603	0.00707	-2.27	0.0386	1.00040

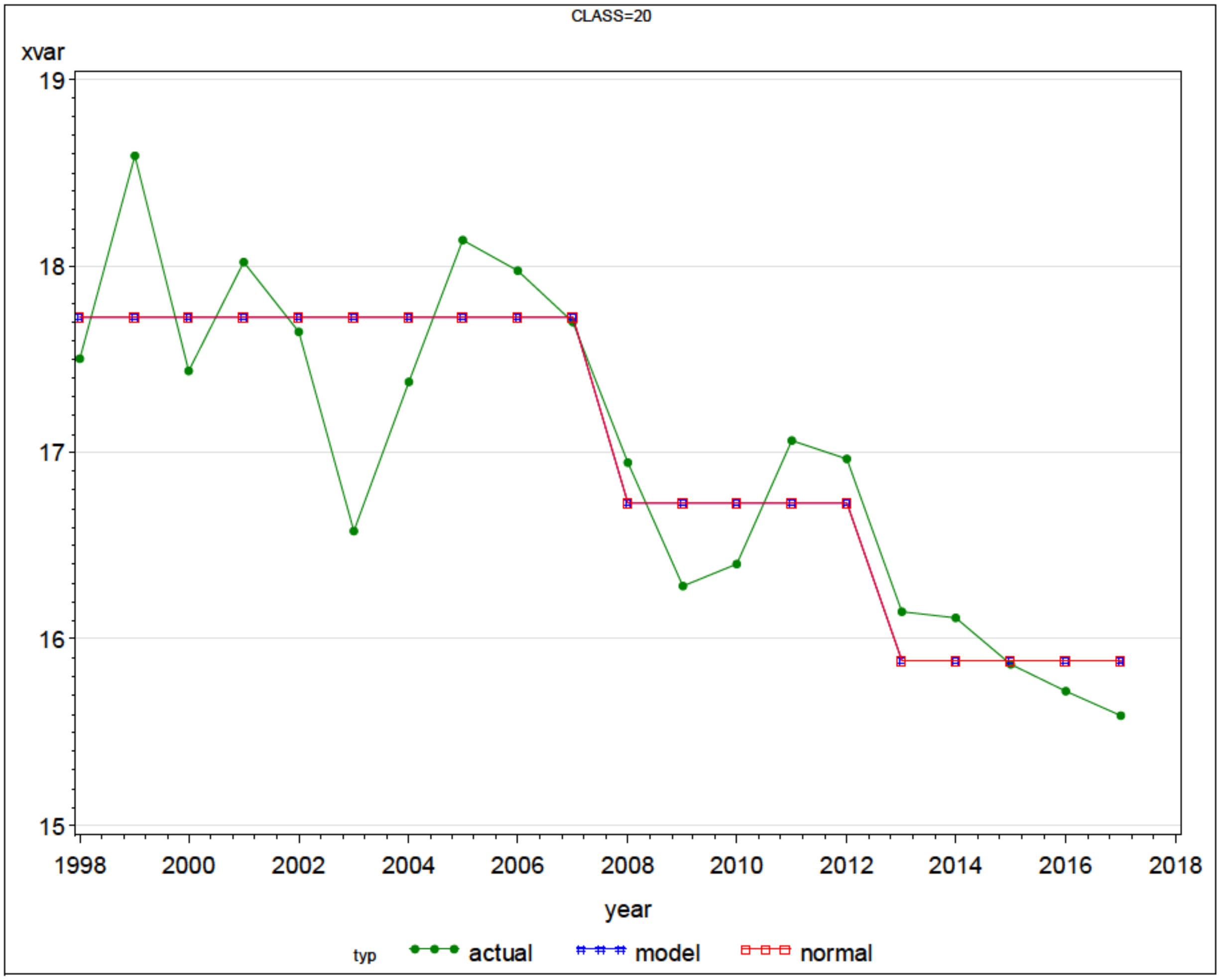
Figure A8: Residential Summer kW per Customer Regression Equation

Root MSE	0.03102	R-Square	0.9781
Dependent Mean	3.62672	Adj R-Sq	0.9740
Coeff Var	0.85544		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.37371	0.08296	28.61	<.0001	0
i98_08	1	0.49447	0.02032	24.33	<.0001	1.50540
i09_12	1	0.27372	0.02280	12.01	<.0001	1.54897
cdh	1	0.00527	0.00044121	11.94	<.0001	1.03613

Figure A9: Commercial Summer kW per Customer Regression Equation

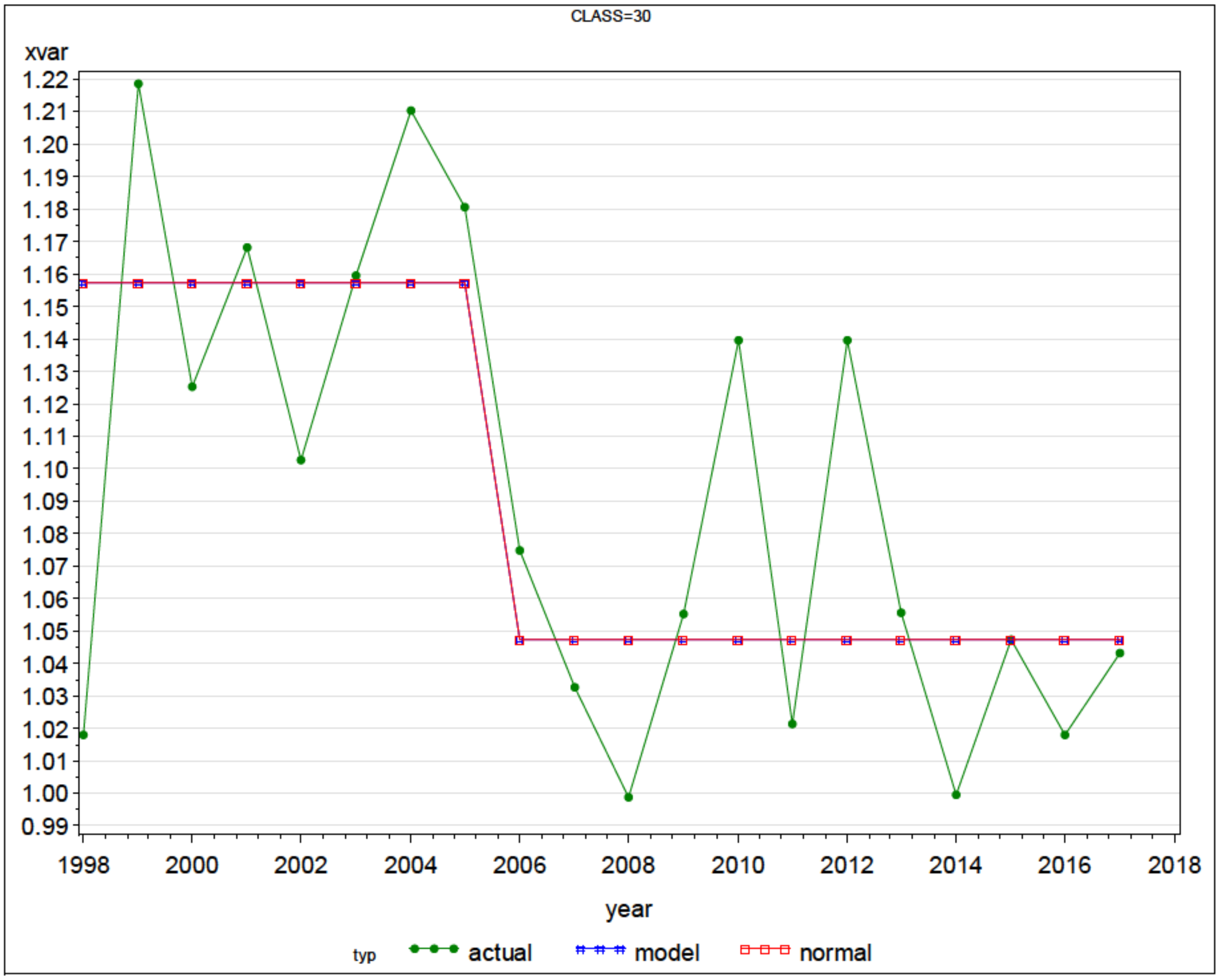


Root MSE	0.38840	R-Square	0.8163
Dependent Mean	16.98935	Adj R-Sq	0.7946
Coeff Var	2.28611		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	15.88726	0.17370	91.47	<.0001	0
i98_07	1	1.83709	0.21563	8.52	<.0001	1.48023
i08_12	1	0.84600	0.24564	3.44	0.0031	1.48023

Figure A10: Industrial Summer kW per kWh Regression Equation

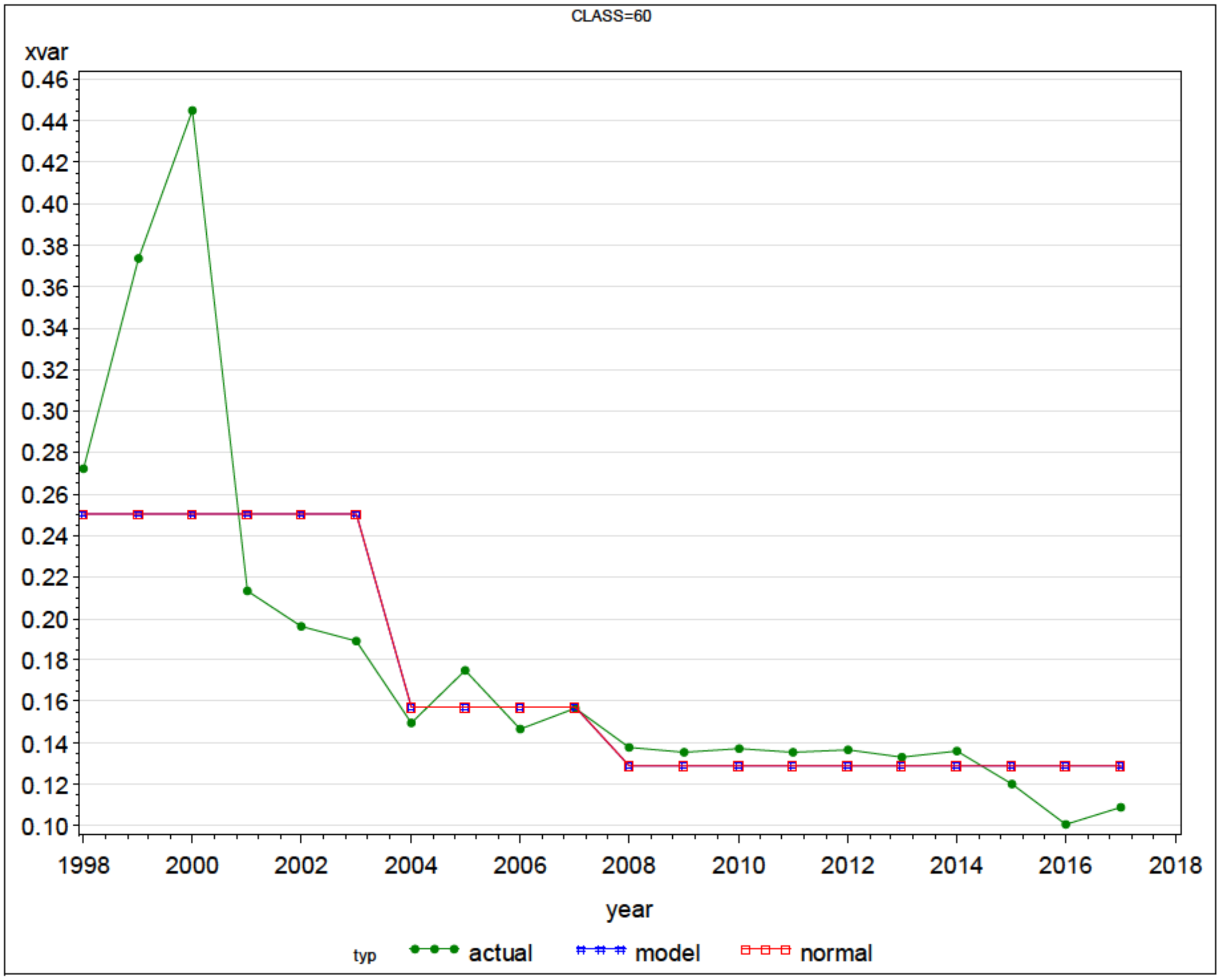


Root MSE	0.04655	R-Square	0.5834
Dependent Mean	1.09088	Adj R-Sq	0.5603
Coeff Var	4.26685		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.04726	0.01381	75.86	<.0001	0
i98_05	1	0.11015	0.02194	5.02	<.0001	1.00000

Figure A11: Public Street Lighting Summer kW per kWh Regression Equation

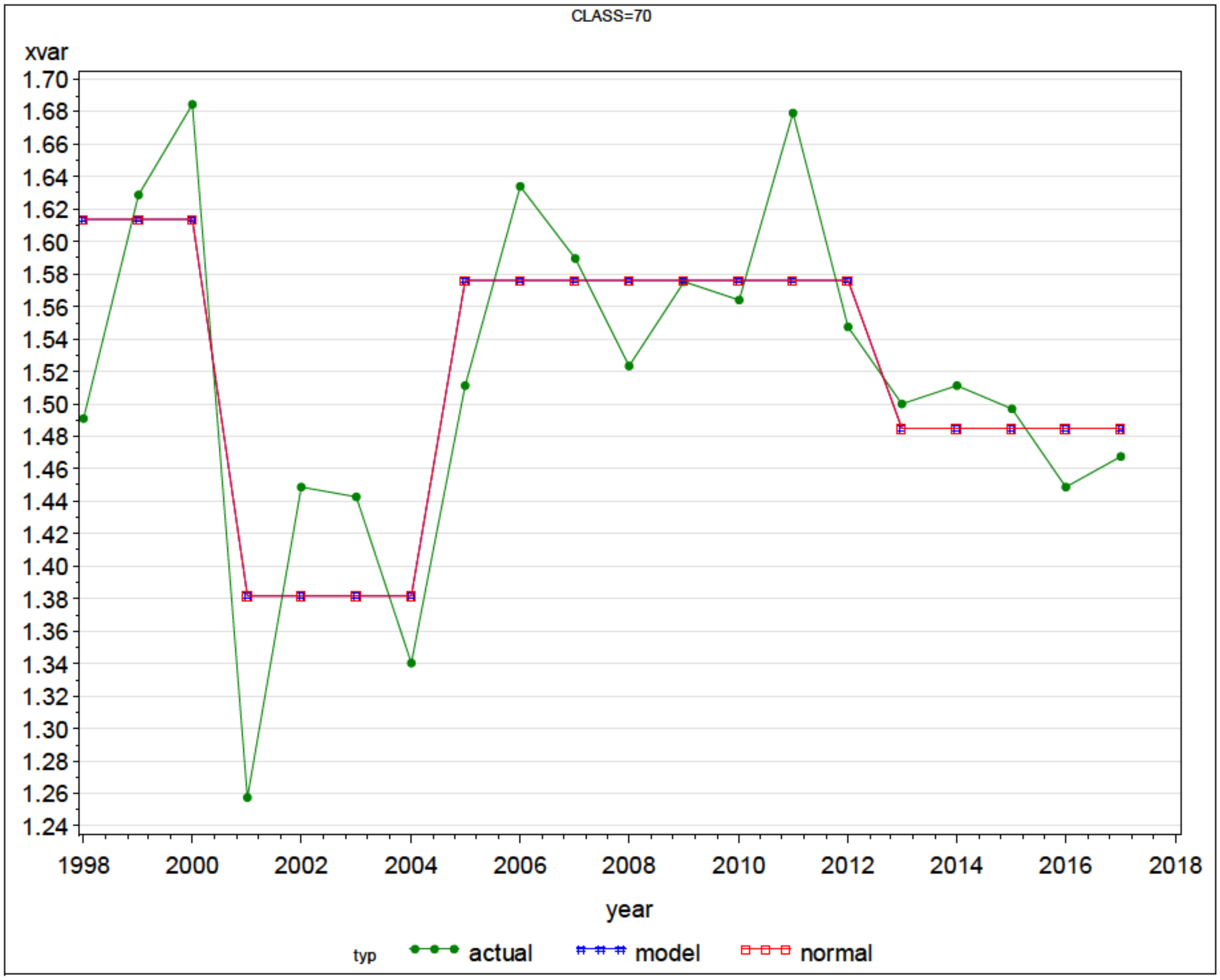


Root MSE	0.02724	R-Square	0.7087
Dependent Mean	0.15512	Adj R-Sq	0.6744
Coeff Var	17.56336		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.12876	0.00871	14.78	<.0001	0
i98_03	1	0.12191	0.01896	6.43	<.0001	1.06530
i04_07	1	0.02826	0.01617	1.75	0.0986	1.06530

Figure A12: Other Public Authorities Summer kW per kWh Regression Equation

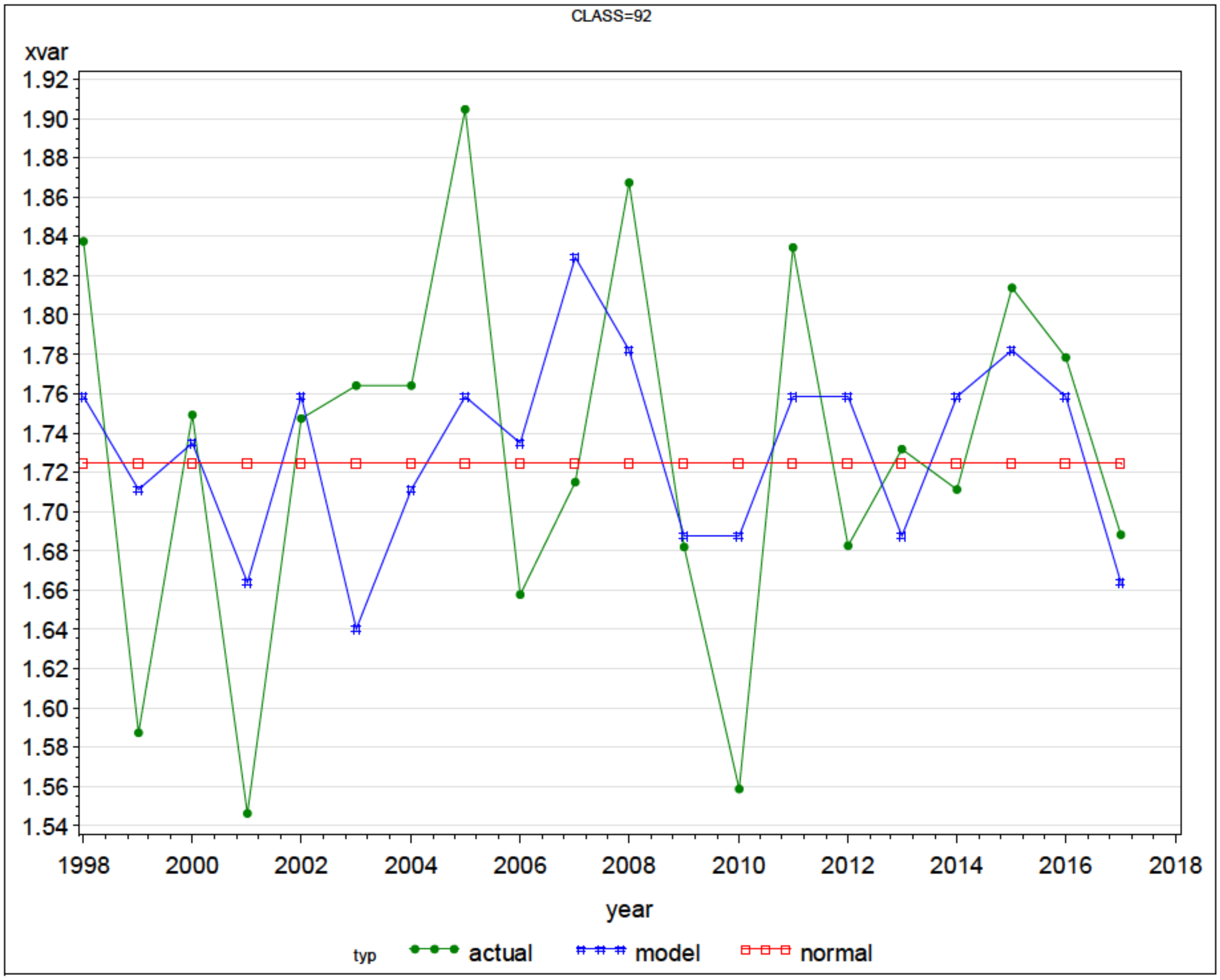


Root MSE	0.06103	R-Square	0.6764
Dependent Mean	1.52037	Adj R-Sq	0.6158
Coeff Var	4.01428		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.48502	0.02729	54.41	<.0001	0
i98_00	1	0.12849	0.04607	2.79	0.0131	1.32424
i01_04	1	-0.10295	0.04187	-2.46	0.0257	1.40488
i05_12	1	0.09095	0.03493	2.60	0.0192	1.52137

Figure A13: Municipal Summer kW per kWh Regression Equation



Root MSE	0.08684	R-Square	0.2443
Dependent Mean	1.73104	Adj R-Sq	0.2023
Coeff Var	5.01673		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.58169	0.95897	-0.61	0.5517	0
maxtmp	1	0.02364	0.00980	2.41	0.0267	1.00000

2018 Reserve Margin Study

Summary

Dominion Energy South Carolina, Inc.'s ("DESC") reserve margin policy is summarized in the following table.

DESC's Reserve Margin Policy		
	Summer	Winter
Base Reserves	12%	14%
Peaking Reserves	14%	21%
Increment for Peaking	2%	7%

The analysis contained in this study reflects that a summer peaking reserve margin of 14.3% and a winter peaking reserve margin of 20.2% is appropriate for DESC and these results support the existing reserve margin policy. Also, the analysis for the base level of reserves to support operation of the system throughout the year outside of seasonal peaking periods reflects that a reserve level of 13.4% in summer and 14.9% in winter is appropriate for DESC. These results also support DESC's existing reserve policy and therefore DESC will maintain the base levels of reserve margin at 12% and 14% in summer and winter respectively.

Introduction

All electric utilities require supply reserves to mitigate the risk of not being able to serve their load requirement because of demand-side related risk and supply-side related risk. Demand-side risk results from uncertainty in the level of demand which can increase because of abnormal weather or other unforeseen circumstances. Supply-side risk results from the possibility of supply resources either not being available at all or their capacity being reduced because of mechanical, fuel, weather or other circumstances. DESC is also required to carry operating reserves sufficient to meet its VACAR reserve sharing agreement. While DESC's share of the VACAR reserves can change each year, it is typically within a few megawatts of 200 MW which is the amount DESC uses in its planning.

Reserve Margin Components
1. VACAR Operating Reserves 2. Demand-Side Risk 3. Supply-Side Risk

In determining its required reserve margin, it is necessary for DESC to analyze the need separately for the cooling season and the heating season. Additionally, within each season it is necessary to distinguish between a peaking need and a base need. There are at least two reasons for this. First, very cold weather can make DESC's winter peak spike for an hour or two. A peak clipping resource available for a few hours may be better suited to address this risk than a generating unit. Second, DESC anticipates a significant amount of solar capacity in its resource portfolio and the ability of solar to serve load can be substantially different during peak summer conditions as opposed to other times during the year.

Demand-Side Risk

The major source of demand-side risk derives from abnormal weather. To quantify the impact of weather on daily peak demands, a regression study was performed for each season separately. Three years of data were combined using the months of June, July, and August for the summer model and December 16 through March 16 for the winter model. The regression study followed the following steps for each season:

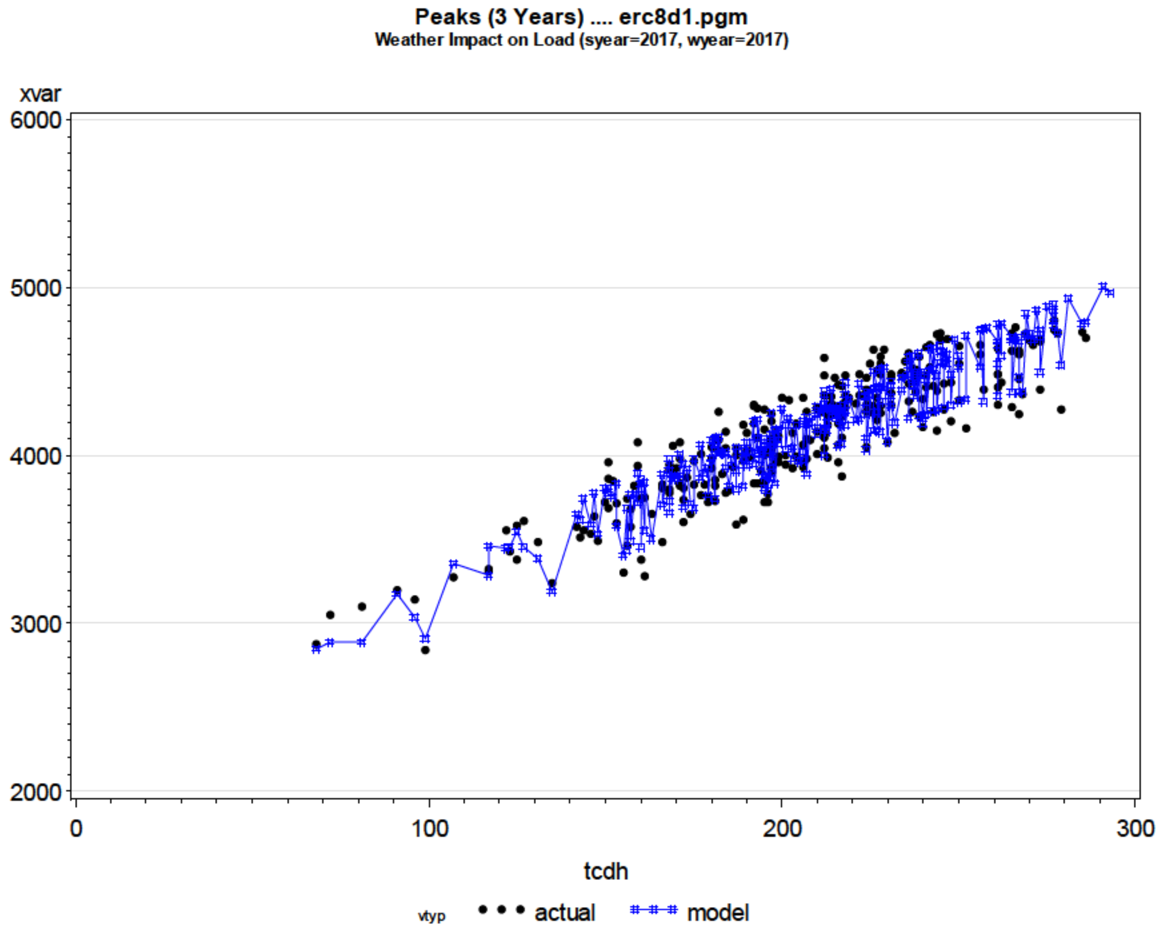
1. Define a set of explanatory variables such as cooling degree hours ("CDH") for summer and heating degree hours for winter ("HDH"). The square of these weather variables was added to the possible choices in case a quadratic equation provided the best fit. To avoid collinearity problems between the linear and squared terms, the deviation from the mean value of both CDH and HDH was used instead of the actual degree hours.
2. The stepwise model selection procedure in SAS[1] was used to find the best set of explanatory variables to use in the regression equation to explain variations in daily peak demand. The stepwise procedure will add or subtract a variable to build the best regression model in terms of goodness of fit. A variable is added to the equation if it meets a specified significance level when added. After adding a variable, the stepwise procedure checks all the variables presently in the regression equation to make sure they meet a certain significance level to stay in the equation. A statistical significance level of 15% was used for both adding a variable and removing a variable. The SAS code that implements this procedure is shown in the appendix with the list of explanatory variables provided.
3. The best model specification chosen by the stepwise procedure was estimated first using a robust regression procedure to identify outliers in the data which are assigned appropriate weights by the modeling procedure. The final estimation of the model was made in a

[1] SAS is a computer programming language used widely in industry to do analytics.

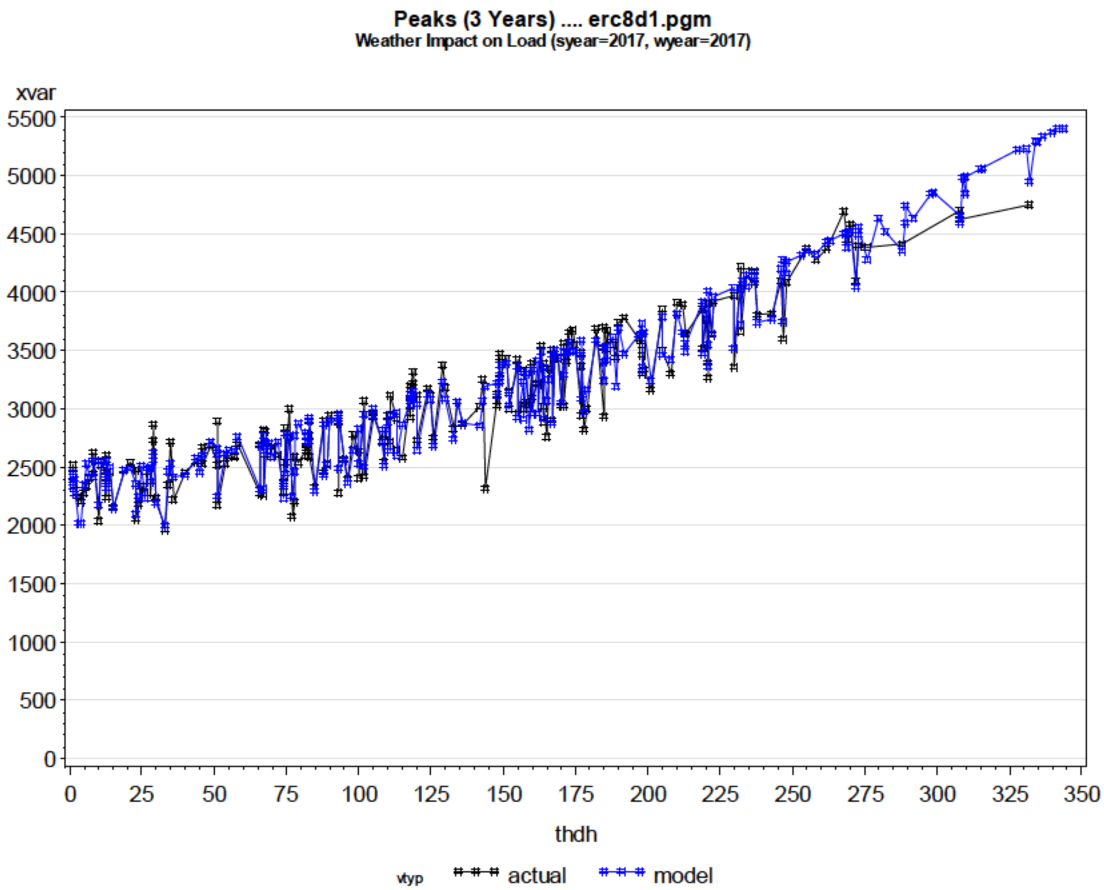
weighted regression analysis using those weights. This mitigated any bias from the squared residuals associated with outliers.

4. The above was first performed for all the days in the summer season for which CDH was greater than zero and in the winter season for which HDH was greater than zero. To estimate a sensitivity to the data, the entire process was repeated using the 100 hottest days in summer based on CDH and the coldest 100 days in winter based on HDH.
5. The stepwise procedure chose a quadratic formulation as the best fitting model in all four instances, i.e. in summer and winter and with all the days and with only the 100 most extreme days. To estimate the sensitivity to the quadratic formulation, a linear model was designed by dropping the quadratic term out of the quadratic model in the 100-day scenario. Thus, DESC estimated three summer models and three winter models.
6. The seasonal peak demand days on the system since 1991 were identified and the weather from those days as well as day of week and month of occurrence were entered into the six regression equations to estimate what the seasonal peak demand would be today if the historical peak conditions were present. For each season, approximately 28 different peak demands were calculated. The average of these seasonal peaks was taken as an approximation of the peak demand under normal weather conditions and the difference between the maximum and the normal represents the seasonal demand side risk, which is the goal of this exercise.

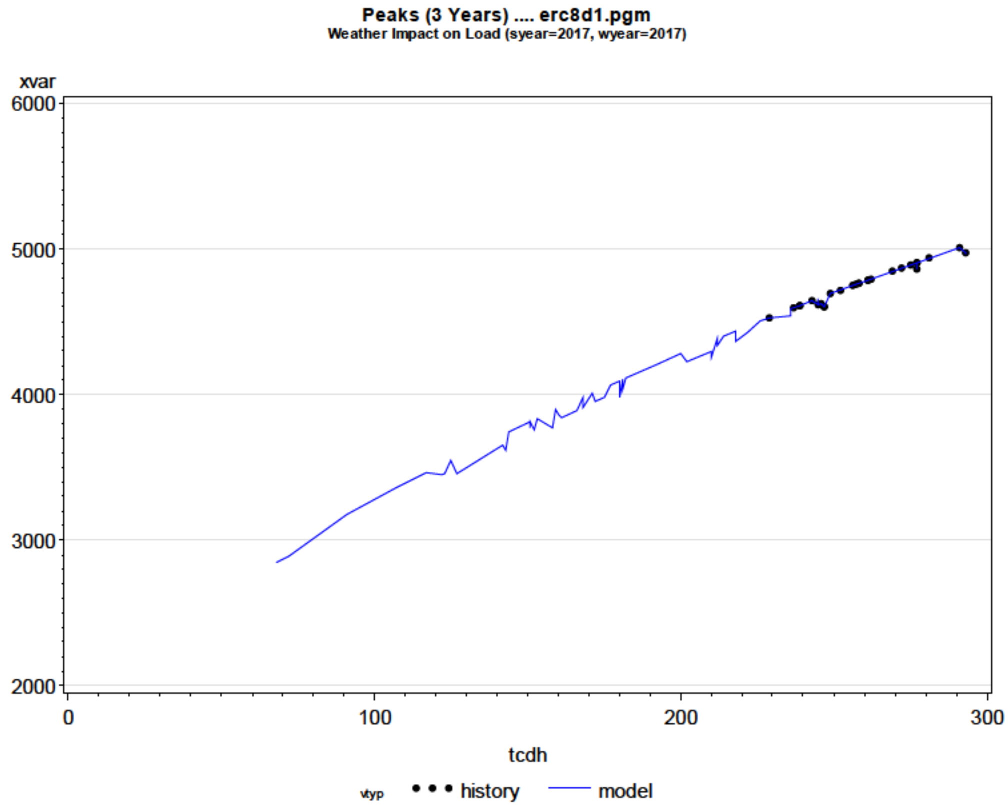
The following chart compares the summer regression model's daily peak estimates to the actual daily peak demands. The estimated regression equations and related statistics are included as appendices.

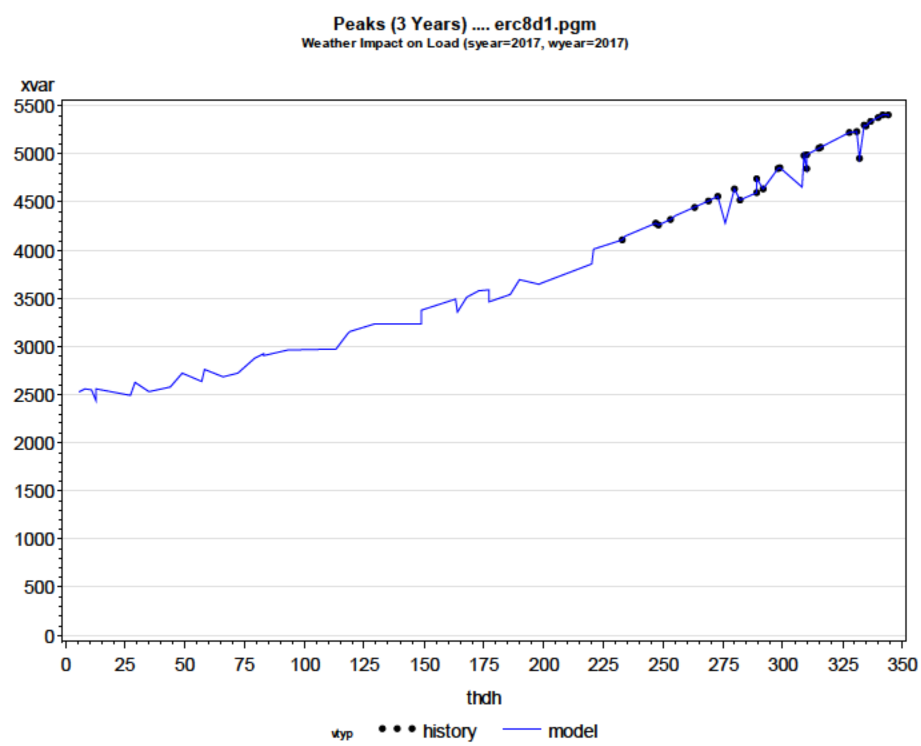


The following chart compares the winter regression model's daily peak estimates to the actual daily peak demands.



The next step used these regression equations to estimate what the peak demand would be on DESC's system today given the weather that occurred on historical peak days since 1991. The following two charts display the regression equation, the resulting peak demands and where they fall along the regression line. The first chart is for the summer season and the second for the winter season.


Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)
xvar
6000
5000
4000
3000
2000
0
100
200
300
tcdh
vtyp
history
model


Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)
xvar
5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
0
25
50
75
100
125
150
175
200
225
250
275
300
325
350
thdh
vtyp
history
model

The following table, Table 1, shows the maximum peak demand that would result from the most extreme weather since 1991. The table also shows the average peak demand which represents the peak demand expected under normal or average weather conditions today. Finally, the table shows the maximum deviation from normal that could occur on DESC's system due to abnormal weather. The results in Table 1 are for the regression models that are based on all the days in the season where degree hours were positive. The results suggest that the summer demand risk is 245 MW while the winter demand risk is 556 MW.

Table 1

MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**
Summer	**5,008**	**4,763**	**245**	**5.1%**
Winter	**5,408**	**4,852**	**556**	**11.5%**

Table 1a shows the results for the two alternate summer models, one quadratic and one linear, and both based on the 100 hottest days in the season. The demand risk based on the quadratic model is 252 MW while for the linear model the demand risk is 292 MW. The linear estimate is higher than the quadratic estimate because the regression procedure estimated a concave down quadratic function, i.e., the impact of weather moderates as the days get hotter.

Table 1a

Summer Models Results Using 100 Hottest Days MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**
Summer Quadratic	**4,900**	**4,648**	**252**	**5.4%**
Summer Linear	**4,954**	**4,662**	**292**	**6.3%**

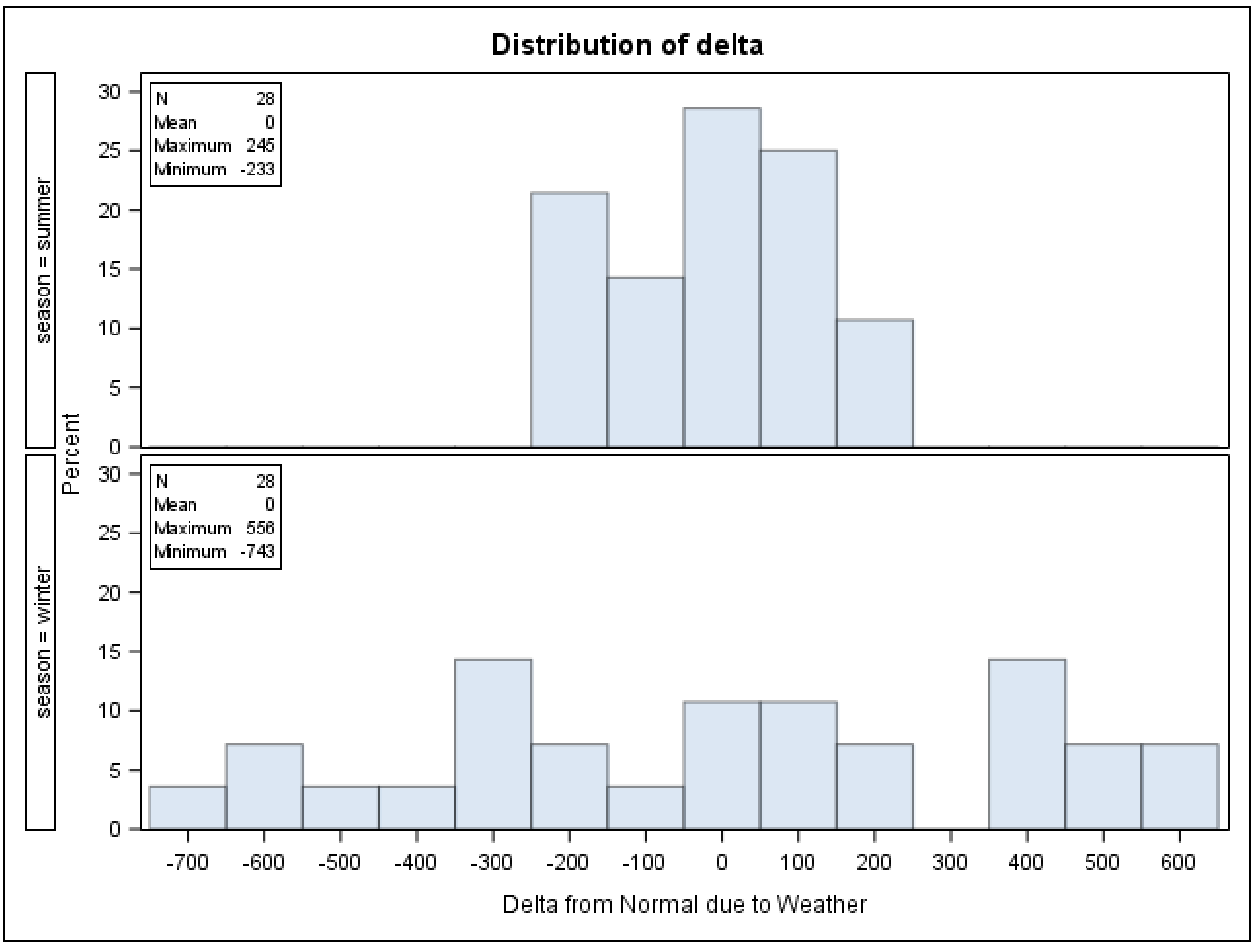
Similar data is presented in Table 1b for the two alternate winter models, again both based on the 100 coldest days in the season. The demand risk based on the quadratic model is 617 MW while for the linear model the demand risk is 509 MW. The linear estimate is lower than the quadratic estimate because the regression procedure estimated a concave up quadratic function, i.e., the impact of weather increases as the days get colder.

Table 1b

Winter Models Results Using 100 Coldest Days MW Peak Demand				
Weather	**Maximum**	**Normal**	**Deviation**	**%Deviation**
Winter Quadratic	**5,484**	**4,867**	**617**	**12.7%**
Winter Linear	**5,292**	**4,783**	**509**	**10.6%**

There are thus three estimates of demand side risk for the summer, i.e. the base level of 245 MWs and the two alternate estimates of 252 MW and 292 MW. For the winter season the base estimate is 556 MW while the two alternates are 617 MW and 509 MW.

The following chart shows the distribution of deviations about the mean using the quadratic model based on all days in the season. The top distribution for the summer period is similar to a normal or bell-shaped probability distribution while the bottom chart representing the weather risk in the winter is more spread out and similar to a uniform probability distribution.



The following table, Table 2, summarizes the risk of higher peak demands based on these distributions.

Table 2

MW Weather Deviations by Percentile				
Percentile	**75%**	**90%**	**95%**	**100%**
Summer	**118**	**173**	**214**	**245**
Winter	**379**	**527**	**553**	**556**

Clearly, winter weather poses a greater demand-side reliability risk than summer since the maximum deviation from a normal weather forecast can reach as much as 556 MW while in summer the maximum deviation is closer to 245 MW.

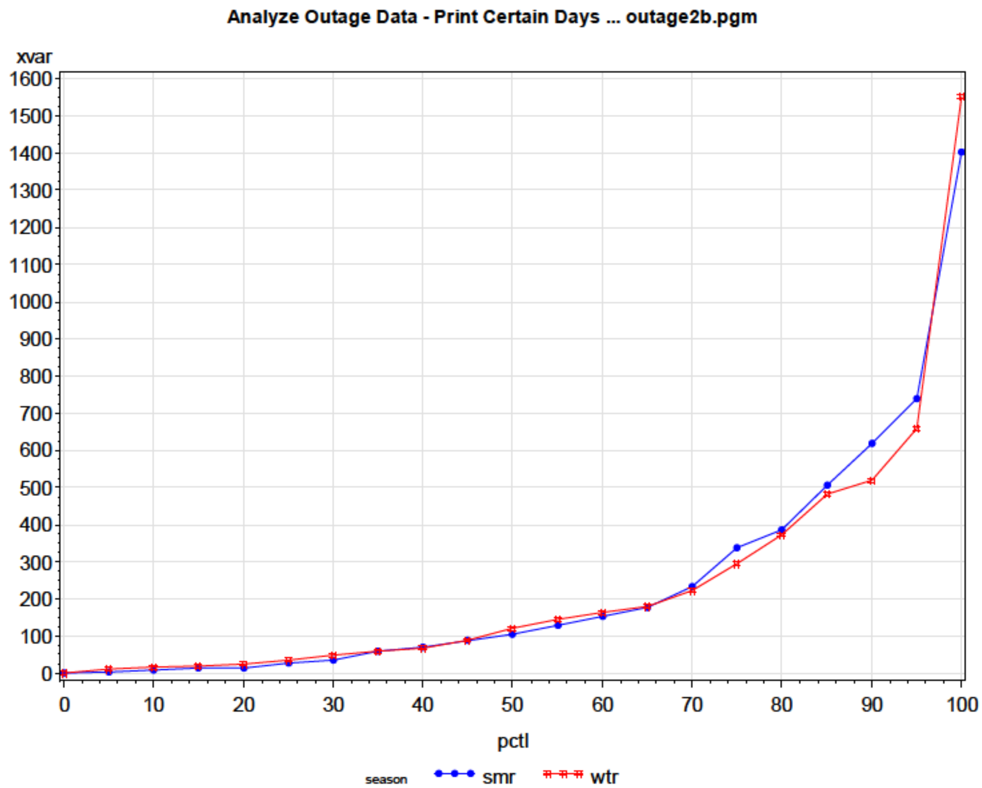
Supply-Side Risk

To quantify the supply-side risk, the forced outage history of DESC's generating units was analyzed. By calculating the number of MWs of generation that was forced out or de-rated on each day of the summer and winter, a distribution of outage was developed for the summer season and for the winter season. For summer, the daily outages during the months of June, July and August were studied for the years 2010-2017. For winter, the months of December, January and February were used. The resulting number of days used for summer and for winter was greater than 700 each season. Table 3 below summarizes each of these distributions of forced outages. For example, in summer it would take 234 MW of reserve capacity to replace the capacity forced out over 70% of the summer days being studied.

Table 3

MW Forced Out by Percentile						
Percentile	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Summer	**106**	**152**	**234**	**385**	**618**	**1,402**
Winter	**121**	**165**	**223**	**373**	**520**	**1,552**

The following is the distribution in graphical form showing the accumulated MW out by the percentile in the probability distribution.



To maintain reliability and replace the loss of generating capacity up to 70% of the days in the winter, DESC estimates that it needs about 223 MW of reserve capacity.

Summary: Reserve Capacity for Summer and Winter Peak Periods

To calculate the required reserve margins for summer and winter peak periods, DESC used the maximum deviation from normal estimated in the demand-side risk analysis and the 70% cutoff value from the outage distributions developed for the summer and winter seasons. The following table summarizes the results.

Table 4

Reserve Margin for Summer and Winter Peak Periods		
	Summer	Winter
VACAR Operating	200	200
Demand-Side Risk	245	556
Supply-Side Risk	234	223
Total Reserve MWs	679	979
Normal Peak Demand	4,763	4,852
Reserve Margin %	14.3%	20.2%
Reserve Margin Policy	14%	21%

DESC's reserve margin policy is to have a level of capacity reserves at least as great as 14% of the normal weather summer peak forecast for the summer season and 21% of the normal weather winter peak forecast for the winter season.

<u>Base Reserve Capacity Needed to Operate the System Reliably Throughout the Year</u>

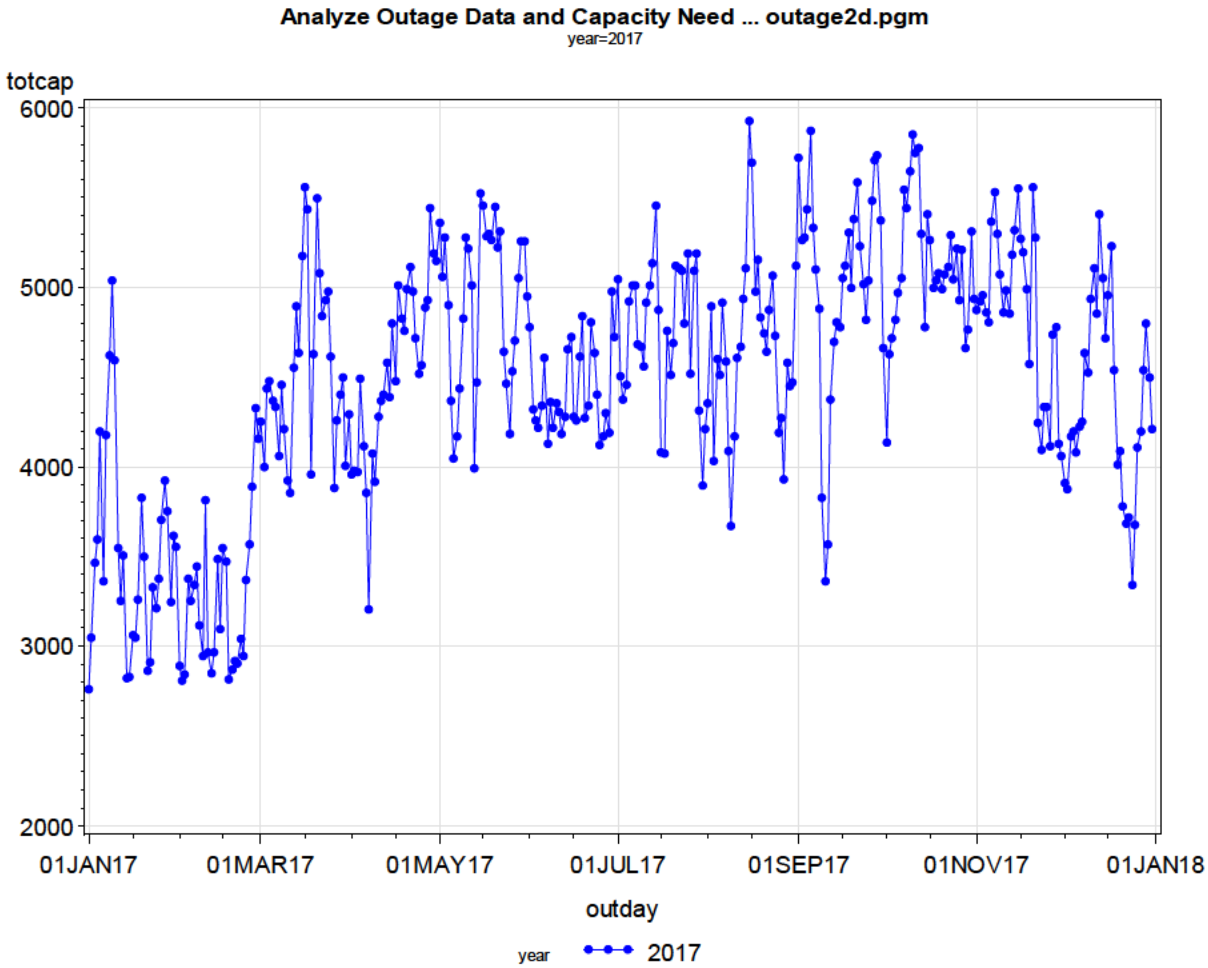
In addition to the reserves needed to address risk during the summer and winter peak periods, DESC needs a portion of this reserve capacity to operate the system throughout the year, not only to meet the load, but also to cover both scheduled and un-scheduled generating unit outages. To quantify this need DESC analyzed its forced and scheduled outages since 2010 and determined the capacity needed each day throughout the year. The basic formula relating available capacity and system need is the following.

$$\text{Total Capacity} - \text{MW Forced Out} - \text{MW Scheduled Out} = \text{Peak Load} + \text{Residual Operating Reserves}$$

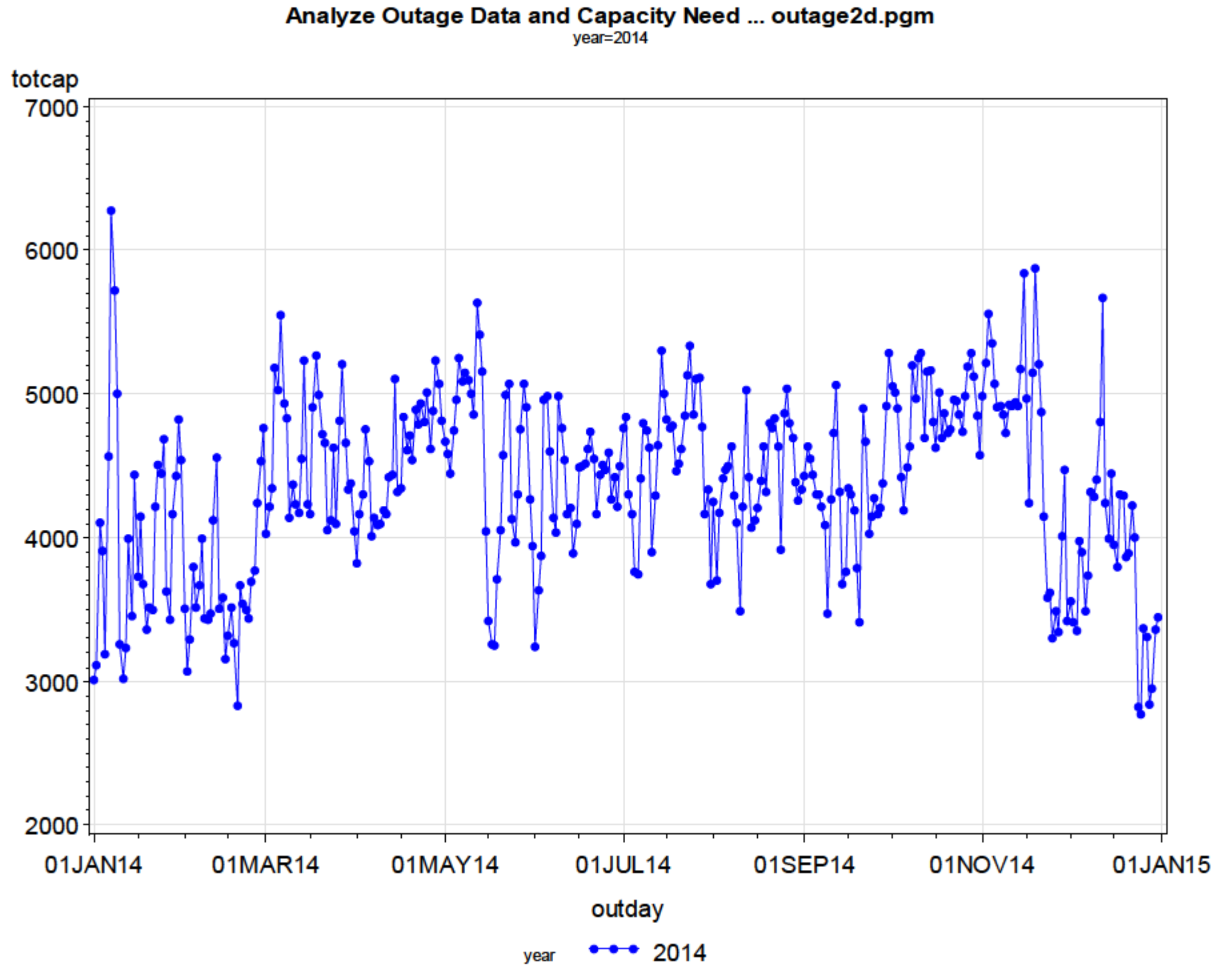
By rearranging terms, the daily capacity need can be calculated with this formula.

$$\text{Total Daily Capacity Needed} = \text{Daily Peak Load} + \text{MW Forced Out} + \text{MW Scheduled Out} + \text{Desired Daily Reserves}$$

Setting the "Desired Daily Reserves" equal to the VACAR Operating Reserve requirement which is about 200 MW, DESC can calculate its daily capacity need by using its historical experience with scheduled and forced outages. Following is a graph of the daily capacity need in 2017.



Below is the chart for 2014 which was the year when an arctic blast of cold air hit the southeast on January 7, 2014. The spike in capacity needed above 6,000 MW was principally caused by the forced outage of Williams Station on that day.



The daily capacity need for each year from 2010 to 2017 was calculated by season. Each year and season were considered a separate distribution of daily need and from each distribution the 95th, 96th, and 97th percentiles were extracted. These percentiles represented the amount of capacity needed to serve 95%, 96%, and 97% of the days in the distribution respectively. The peak days in the distribution, defined as the top 10 to 20 days of highest capacity need, correspond to a demarcation at the 95th and 97th percentile i.e. 10/365 is about 3% and 20/365 is about 5% of the days in the year or stated differently 355/365 is about 97% and 345/365 is about 95%. The individual years and seasons are shown in Appendix C in tabular form. The table below shows the average of these percentiles from the seven years studied. For example, in the summer, DESC needs about 5,309 MW of capacity to serve 95% of the days in the summer period while 5,406 MW is needed to serve 97% of the days in the winter period. Since this level of capacity is needed to serve most of the days of the year, DESC considers this a base level of capacity.

Table 5

Distribution of Daily Capacity Need at Certain Percentiles (MW)				
Percentile	95%	96%	97%	100%
Summer	5,309	5,359	5,406	5,735
Winter	5,148	5,217	5,333	5,723

In the following table, the base level of capacity is expressed as a percentage of the average maximum customer load occurring in the particular season. Averaging the percentages for the 95th and the 97th percentile yields 13.40% for summer and 14.95% for winter. DESC believes these results support the existing base reserve capacity need in summer of 12% of summer peak demand and in winter, 14% of winter peak demand.

Table 6

Daily Capacity Need Percentiles as Percent of Peak Load				
Percentile	95%	96%	97%	100%
Summer	12.4	13.5	14.4	21.4
Winter	12.9	14.4	17.0	25.6

Conclusion

For the summer months which include May through October, DESC requires base reserves in the amount of 12% of the summer peak load to operate the system reliably and 14% of summer peak load during the peak load periods. For the winter months of November through April, DESC requires 14% of the winter peak load forecast in base reserves to operate the system reliably and 21% for the peak load periods. The following table summarizes DESC's reserve margin policy.

Table 7

DESC's Reserve Margin Policy		
	Summer	Winter
Base Reserves	12%	14%
Peaking Reserves	14%	21%
Increment for Peaking	2%	7%

APPENDICES

Appendix A1- Stepwise Selection Results for Best Model in the Summer Season

Following is the SAS programming code showing the variables used in the stepwise variable selection process that identified the best regression model to use. The first set of SAS results are based on all days in the summer season while the second set is restricted to the 100 hottest days in the season.

```
proc reg;
model mxload=ihol wkend cdh cdh2
        yrlag1 yrlag2 imo6-imo8 idow1-idow7
  /slstay=0.15 slentry=0.15 selection=stepwise ss2 sse aic;
```

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	cdh		1	0.8106	0.8106	408.727	1172.53	<.0001
2	wkend		2	0.0754	0.8860	139.715	180.58	<.0001
3	imo6		3	0.0081	0.8941	112.642	20.77	<.0001
4	ihol		4	0.0079	0.9020	86.3367	21.77	<.0001
5	yrlag1		5	0.0061	0.9081	66.3849	17.94	<.0001
6	yrlag2		6	0.0120	0.9200	25.3887	40.25	<.0001
7	cdh2		7	0.0042	0.9242	12.4056	14.74	0.0002
8	idow6		8	0.0018	0.9260	8.1142	6.31	0.0126

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	cdh		1	0.8653	0.8653	145.354	629.58	<.0001
2	wkend		2	0.0706	0.9359	20.8063	106.92	<.0001
3	idow6		3	0.0094	0.9453	6.0321	16.43	0.0001
4	cdh2		4	0.0034	0.9487	1.9710	6.26	0.0141
5	ihol		5	0.0020	0.9506	0.4719	3.72	0.0569

Appendix A2

Best Regression Equation for Daily Summer Peak Demand Using All Days in the Season

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	304
Number of Observations Used	276
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	36958412	4619801	440.80	<.0001
Error	267	2798296	10481		
Corrected Total	275	39756708			

Root MSE	102.37437	R-Square	0.9296
Dependent Mean	4116.35770	Adj R-Sq	0.9275
Coeff Var	2.48701		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4314.05871	13.82104	312.14	<.0001	0
ihol	1	-309.29412	59.87563	-5.17	<.0001	1.01487
wkend	1	-252.57647	14.42786	-17.51	<.0001	1.09179
cdh	1	8.87928	0.17995	49.34	<.0001	1.40974
cdh2	1	-1.04225	0.25947	-4.02	<.0001	1.15437
yrlag1	1	-127.38431	16.87435	-7.55	<.0001	1.63914
yrlag2	1	-106.65340	15.91125	-6.70	<.0001	1.45026
imo6	1	-70.01001	13.60334	-5.15	<.0001	1.05026
idow6	1	-44.79588	18.42714	-2.43	0.0157	1.07727

Appendix A3

Best Regression Equation for Daily Summer Peak Demand Using 100 Hottest Days

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	16342711	3268542	388.89	<.0001
Error	94	790053	8404.81960		
Corrected Total	99	17132764			

Root MSE	91.67780	R-Square	0.9539
Dependent Mean	4169.53027	Adj R-Sq	0.9514
Coeff Var	2.19876		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4272.15775	14.07452	303.54	<.0001	0
ihol	1	-202.30607	97.28648	-2.08	0.0403	1.11453
wkend	1	-282.53890	22.25120	-12.70	<.0001	1.08378
cdh	1	8.71227	0.23552	36.99	<.0001	1.15184
cdh2	1	-0.93290	0.38207	-2.44	0.0165	1.13206
idow6	1	-99.93867	27.37706	-3.65	0.0004	1.12739

Appendix A4

Linear Regression Equation for Daily Summer Peak Demand Using 100 Hottest Days

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	16370772	4092693	457.22	<.0001
Error	95	850370	8951.25977		
Corrected Total	99	17221142			

Root MSE	94.61110	R-Square	0.9506
Dependent Mean	4165.91046	Adj R-Sq	0.9485
Coeff Var	2.27108		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4254.01278	12.45681	341.50	<.0001	0
ihol	1	-224.08993	99.85492	-2.24	0.0271	1.10254
wkend	1	-279.47519	22.75927	-12.28	<.0001	1.07635
cdh	1	8.90539	0.23218	38.36	<.0001	1.04926
idow6	1	-100.91267	28.19402	-3.58	0.0005	1.12780

Appendix B1- Stepwise Selection Results for Best Model in the Winter Season

Following is the SAS programming code showing the variables used in the stepwise variable selection process that identified the best regression model to use. The first set of SAS results are based on all days in the winter season while the second set is restricted to the 100 coldest days in the season.

```
proc reg;
model mxload=wtr18 wtr17 wtr16 ihol wkend hdh hdh2
        yrlag1 yrlag2 imo1 imo2 imo3 idow1-idow7
  /slstay=0.15 slentry=0.15 selection=stepwise ss2 sse aic;
```

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	hdh		1	0.8352	0.8352	532.253	1120.02	<.0001
2	wkend		2	0.0725	0.9077	203.735	172.83	<.0001
3	hdh2		3	0.0219	0.9296	106.044	68.00	<.0001
4	ihol		4	0.0069	0.9365	76.6485	23.63	<.0001
5	yrlag1		5	0.0052	0.9416	55.0161	19.28	<.0001
6	imo1		6	0.0036	0.9452	40.7737	14.05	0.0002
7	imo2		7	0.0039	0.9491	24.9199	16.55	<.0001
8	wtr18		8	0.0031	0.9522	12.7940	13.88	0.0002
9	yrlag2		9	0.0013	0.9535	9.0749	5.74	0.0174
10	idow3		10	0.0005	0.9540	8.6530	2.45	0.1191

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	hdh		1	0.7535	0.7535	230.492	299.51	<.0001
2	wkend		2	0.1388	0.8923	48.6584	125.00	<.0001
3	imo1		3	0.0067	0.8990	41.7633	6.38	0.0132
4	ihol		4	0.0067	0.9057	34.8551	6.78	0.0107
5	imo2		5	0.0060	0.9117	28.8815	6.41	0.0130
6	wtr18		6	0.0049	0.9166	24.3910	5.47	0.0215
7	idow4		7	0.0033	0.9199	22.0204	3.79	0.0545
8	yrlag2		8	0.0036	0.9236	19.1870	4.35	0.0399
9	yrlag1		9	0.0071	0.9307	11.8382	9.16	0.0032
10	idow5		10	0.0022	0.9328	10.9465	2.89	0.0924
11	hdh2		11	0.0019	0.9347	10.4392	2.55	0.1137

Appendix B2

Best Regression Equation for Daily Winter Peak Demand Using All Days in the Season

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	251
Number of Observations Used	223
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	82329996	9147777	701.23	<.0001
Error	213	2778673	13045		
Corrected Total	222	85108669			

Root MSE	114.21652	R-Square	0.9674
Dependent Mean	3070.71806	Adj R-Sq	0.9660
Coeff Var	3.71954		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3077.82868	20.10871	153.06	<.0001	0
wtr18	1	-315.82025	71.15093	-4.44	<.0001	1.44678
ihol	1	-401.70093	59.45998	-6.76	<.0001	1.03161
wkend	1	-376.03592	17.59272	-21.37	<.0001	1.04141
hdh	1	7.17788	0.11225	63.94	<.0001	1.29907
hdh2	1	1.40804	0.13546	10.39	<.0001	1.38861
yrlag1	1	-123.94243	19.80997	-6.26	<.0001	1.43720
yrlag2	1	-64.29258	20.10490	-3.20	0.0016	1.43045
imo1	1	144.31807	19.91338	7.25	<.0001	1.51943
imo2	1	120.63311	20.44786	5.90	<.0001	1.42949

Appendix B3

Best Regression Equation for Daily Winter Peak Demand Using 100 Coldest Days

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	21605105	1964100	127.98	<.0001
Error	88	1350561	15347		
Corrected Total	99	22955667			

Root MSE	123.88418	R-Square	0.9412
Dependent Mean	3623.34836	Adj R-Sq	0.9338
Coeff Var	3.41905		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3662.44166	36.09219	101.47	<.0001	0
wtr18	1	-356.50387	94.87557	-3.76	0.0003	2.24954
ihol	1	-435.52549	128.52510	-3.39	0.0011	1.06526
wkend	1	-355.02221	29.57414	-12.00	<.0001	1.22204
hdh	1	9.36800	0.39523	23.70	<.0001	1.84796
hdh2	1	1.30843	0.80204	1.63	0.1064	2.90784
yrlag1	1	-106.43984	35.24151	-3.02	0.0033	1.47493
yrlag2	1	-98.67824	32.57139	-3.03	0.0032	1.56975
imo1	1	151.79067	33.96911	4.47	<.0001	1.82665
imo2	1	138.28224	37.92080	3.65	0.0004	1.61805
idow4	1	129.82219	44.63422	2.91	0.0046	1.16459
idow5	1	73.62491	41.37926	1.78	0.0786	1.17357

Appendix B4

Linear Regression Equation for Daily Winter Peak Demand Using 100 Coldest Days

Peaks (3 Years) erc8d1.pgm
Weather Impact on Load (syear=2017, wyear=2017)

The REG Procedure
Model: MODEL1
Dependent Variable: mxload

Number of Observations Read	128
Number of Observations Used	100
Number of Observations with Missing Values	28

Weight: wgts Weight

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	21630957	2163096	137.39	<.0001
Error	89	1401264	15745		
Corrected Total	99	23032221			

Root MSE	125.47723	R-Square	0.9392
Dependent Mean	3622.83771	Adj R-Sq	0.9323
Coeff Var	3.46351		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3683.49549	34.38143	107.14	<.0001	0
wtr18	1	-265.97943	76.53139	-3.48	0.0008	1.42695
ihol	1	-463.11021	129.08845	-3.59	0.0005	1.04753
wkend	1	-357.38178	29.85925	-11.97	<.0001	1.21722
hdh	1	9.63809	0.37173	25.93	<.0001	1.59300
yrlag1	1	-102.01486	35.49664	-2.87	0.0051	1.46661
yrlag2	1	-110.16577	32.27602	-3.41	0.0010	1.50360
imo1	1	161.91774	33.47049	4.84	<.0001	1.73247
imo2	1	137.88242	38.29822	3.60	0.0005	1.60778
idow4	1	117.78909	44.56174	2.64	0.0097	1.13181
idow5	1	71.81312	41.87812	1.71	0.0899	1.17208

Appendix C:

Daily Capacity Need by Year and Season for Certain Percentiles in the Distribution

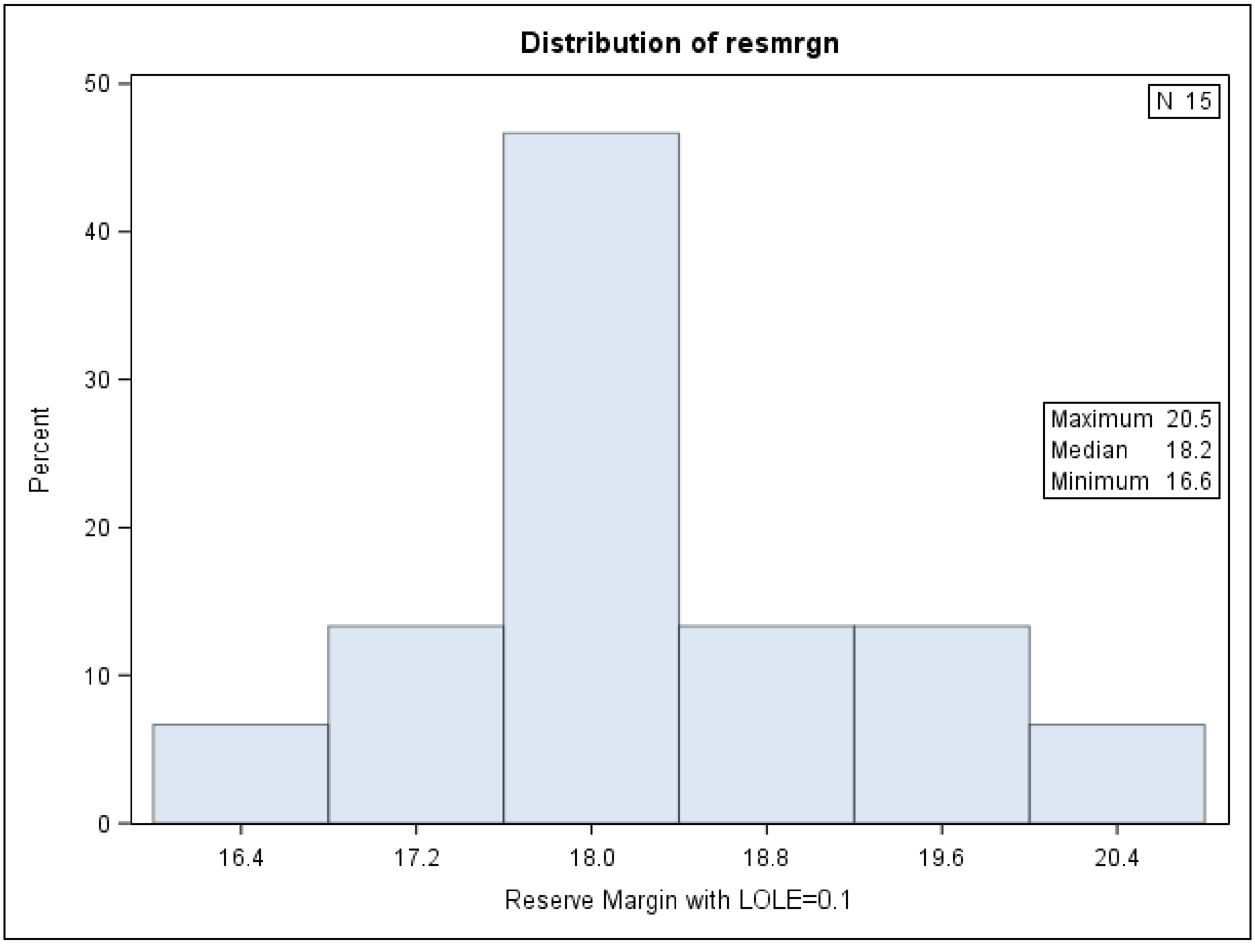
Analyze Outage Data and Capacity Need ... outage2d.pgm

seas	wyear	ndys	mxcap	mxload	cap95	cap96	cap97	mxresm	mxresm 95	mxresm 96	mxresm 97
summer	2010.0	184.0	5778.0	4735.0	5268.0	5322.0	5418.0	22.0	11.3	12.4	14.4
	2011.0	184.0	5697.5	4885.0	5418.5	5470.0	5492.0	16.6	10.9	12.0	12.4
	2012.0	184.0	6181.5	4761.0	5224.5	5256.5	5299.5	29.8	9.7	10.4	11.3
	2013.0	184.0	5645.0	4574.0	5264.0	5306.0	5392.5	23.4	15.1	16.0	17.9
	2014.0	184.0	5636.5	4594.0	5195.5	5254.5	5286.5	22.7	13.1	14.4	15.1
	2015.0	184.0	5386.0	4750.0	5115.0	5167.0	5197.5	13.4	7.7	8.8	9.4
	2016.0	184.0	5631.5	4807.0	5343.0	5393.5	5425.5	17.2	11.2	12.2	12.9
	2017.0	184.0	5927.5	4697.0	5646.5	5705.5	5734.5	26.2	20.2	21.5	22.1
summer		184.0	5735.4	4725.4	5309.4	5359.4	5405.8	21.4	12.4	13.5	14.4
======		======	======	======	======	======	======	======	======	======	======
winter	2010.0	181.0	5285.0	4718.0	5008.0	5049.0	5102.0	12.0	6.1	7.0	8.1
	2011.0	181.0	5641.5	4868.0	5017.5	5043.0	5135.0	15.9	3.1	3.6	5.5
	2012.0	182.0	5832.5	4397.0	5316.0	5379.0	5426.5	32.6	20.9	22.3	23.4
	2013.0	181.0	5958.5	3984.0	4920.5	5078.0	5389.5	49.6	23.5	27.5	35.3
	2014.0	181.0	6272.5	4853.0	5235.0	5349.5	5560.5	29.2	7.9	10.2	14.6
	2015.0	181.0	5601.5	4970.0	5082.0	5116.5	5251.5	12.7	2.3	2.9	5.7
	2016.0	182.0	5632.0	4409.0	5286.5	5315.5	5357.0	27.7	19.9	20.6	21.5
	2017.0	181.0	5561.0	4457.0	5316.0	5406.0	5442.5	24.8	19.3	21.3	22.1
winter		181.3	5723.1	4582.0	5147.7	5217.1	5333.1	25.6	12.9	14.4	17.0
======		======	======	======	======	======	======	======	======	======	======

Loss of Load Expectation Study

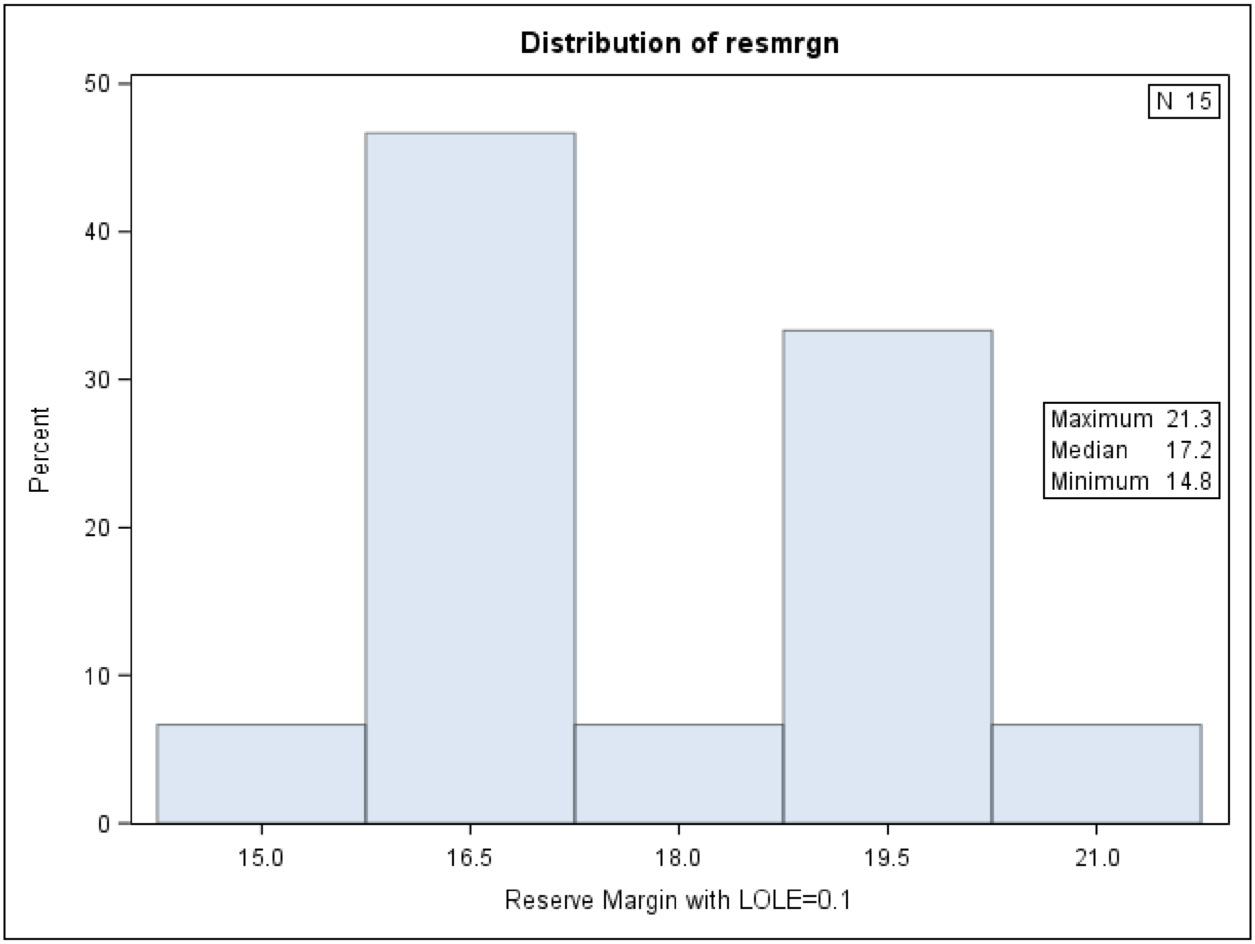
Executive Summary

The Loss of Load Expectation ("LOLE") reliability index was calculated using the adjusted profiles from the last 15 years, 2004-2018. The goal of the study was to calculate the relationship on Dominion Energy South Carolina, Inc.'s ("DESC") system between reserve margin and LOLE, thereby deriving the reserve margin equivalent to an LOLE=0.1. Two studies were run: one using an adjustment based on seasonal peaks, the "peak" method, and a second using an adjustment based on energy, the "energy" method. The following histogram summarize the results when using the peak method.



This histogram reflects that a reserve margin between 16.6% and 20.5% is required to achieve reliability at the level represented by an LOLE=0.1, i.e., one day in 10 years. The average, or middle point, in the distribution is 18.2%.

The following histogram summarizes the results when using the energy method.



This histogram reflects that a reserve margin between 14.8% and 21.3% is required to achieve reliability at the level represented by an LOLE=0.1, i.e., one day in 10 years. The average, or middle point, in the distribution is 17.2%.

Since the LOLE index represents reliability for the entire year and is calculated using peak loads on each day of the year, it should be used to evaluate DESC's base reserve margin policy, i.e., having a minimum reserve margin of 14% throughout the winter season and 12% throughout the summer season. As explained later in this report, it is not appropriate to use LOLE to assess risk during extreme weather events. Using the LOLE methodology, a 14% reserve margin equates to about an LOLE=0.3, i.e., 3 days in 10 years. However, DESC mitigates much of this apparent risk, i.e., 0.3 vs 0.1 LOLE, by its use of peaking reserves which are expected to be available for a few peak days each season.

Introduction

The LOLE methodology essentially consists of three steps: 1) prepare the normalized daily peak load data; 2) calculate the capacity outage probability table ("COPT") which associates a probability to a level of outage; and 3) using the daily peaks and the COPT compute the expected number of days of outage, i.e., the LOLE index. The industry standard for reliability sets the LOLE at 0.1 which equates to an expectation of 1 day of outage every 10 years and is known as the "1 in 10" criterion.

It is worth noting that the term loss of load probability ("LOLP") is often used interchangeably with LOLE although strictly speaking LOLP is a probability and LOLE is an expected value.

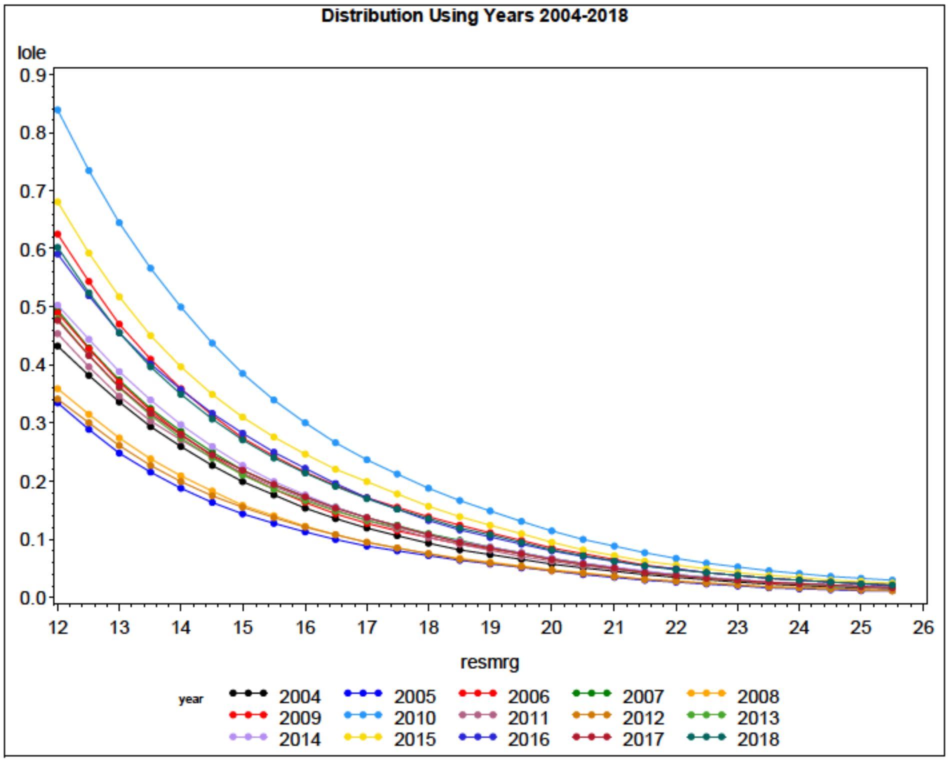
The Details

The daily peak load data was calculated for each of the last 15 years, i.e., 2004 through 2018, under two adjustment scenarios. The first type of adjustment, the "peak" method, adjusted the daily loads from history so that their summer and winter peaks were equal to those projected for 2019, that is, the adjustment factor for daily peaks in the summer months was the ratio of the 2019 summer peak over the historical years summer peak and a similar adjustment for winter months using winter peaks. The second method, the "energy" method, adjusted historical daily peaks by the ratio of the 2019 forecasted system energy by the system energy occurring in the historical year. Summary results of these adjustments are shown in Table 1 of the appendix.

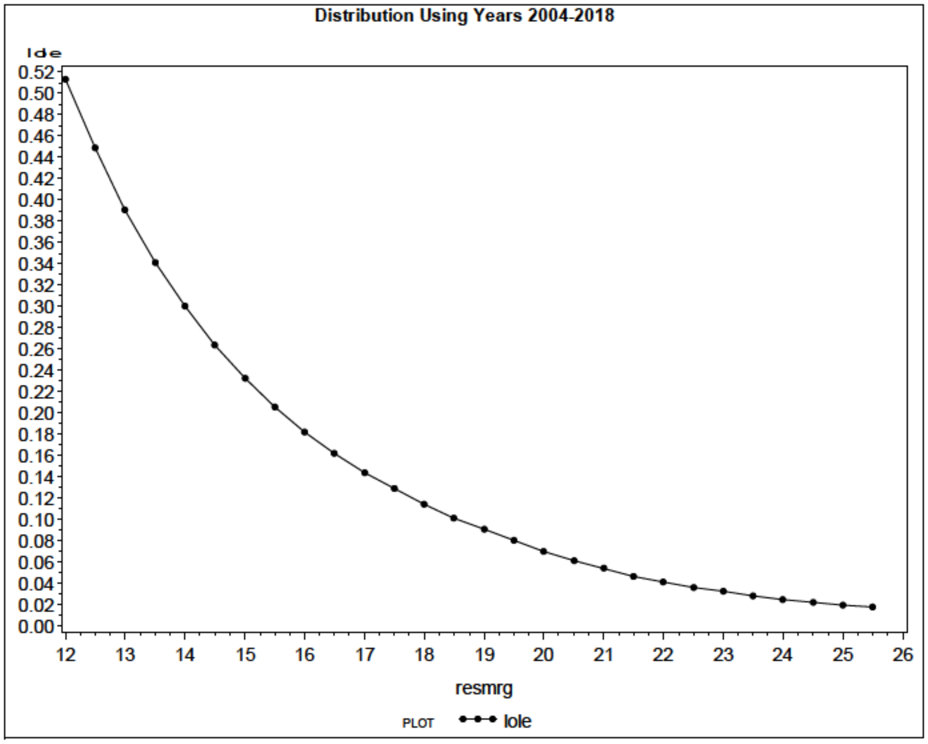
The COPT was calculated from the Company's forced outage data for the years 2010 through 2017. The forced outage rate of each generating unit was calculated and then averaged over the 8 years. The result was the effective forced outage rate, ("EFOR"), from which the COPT was created. A few small gas turbines ("GT") did not have acceptable data and their EFOR was set to 5%. Each unit is considered either available or unavailable with the probability of being unavailable equal to the EFOR. Thus, the outage status of each unit can be described by a binomial probability distribution with parameter EFOR. In this way a total of 65 binomial distributions are set up, one for each unit. To create the COPT, these probability distributions are combined using the convolution algorithm from statistical theory. The convolution algorithm requires the individual probability distributions to be statistically independent. For the most part generating units are mechanically independent, but their availability is not statistically independent since several units can be affected simultaneously by severe weather or fuel restrictions. Nevertheless, the COPT is calculated under the assumption that this independence technicality has minor influence. A summary version of the COPT table is shown as Table 2 in the appendix.

The next step was to use the daily peak loads from each year, one year at a time, and the COPT to calculate the LOLE index. Since the goal was to establish a relationship between reserve margin and LOLE on the DESC system, the LOLE was calculated using values of reserve margin ranging from 12% to 25% in 0.5% steps. Thus, the LOLE associated with 28 different values of reserve margin was computed for each year from 2004 to 2018. The results of these calculations are shown in Tables 3 and 4 in the appendix.

The following graph shows the relationship between reserve margin on the horizontal and the LOLE index shown on the vertical for each year in the study. This graph is for the "peak method" of adjustment. The graph for the "energy method" of adjustment would look similar.



The following graph shows the average LOLE value for each reserve margin level.



The functional relationship between LOLE and reserve margin is not linear but the relationship between the LOG(LOLE) and reserve margin is linear. The logarithm function, LOG( ), used here is the natural logarithm, i.e., with the transcendental number "e" for base. Below are the results of fitting this functional form to the data.

The REG Procedure
Model: MODEL1
Dependent Variable: resmrg

Number of Observations Read	29
Number of Observations Used	28
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	456.62783	456.62783	97176.7	<.0001
Error	26	0.12217	0.00470		
Corrected Total	27	456.75000			

Root MSE	0.06855	R-Square	0.9997
Dependent Mean	18.75000	Adj R-Sq	0.9997
Coeff Var	0.36559		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	9.23069	0.03317	278.28	<.0001
lnlole	1	-4.01300	0.01287	-311.73	<.0001

The parameter estimates in the function can be used to calculate the reserve margin level associated with an LOLE=0.1. Here are the calculations:

Reserve Margin = a + b * LOG(LOLE)
= 9.23069 – 4.01300 * LOG (0.1)
= 9.23069 – 4.01300 * (-2.30259)
= 18.5

Thus, based on the average LOLE data, an LOLE value of 0.1 requires about an 18.5% reserve margin. The equation can also be used to find the LOLE for a given reserve margin by reversing the solution process. For example, it is easy to show that DESC's base winter reserve margin level of 14% is associated with an LOLE=0.3 or about a 3 day in 10 LOLE level.

This same analysis using the average LOLE value for each reserve margin level can be made for the "energy method" of adjustment. The regression results are as follows:

The REG Procedure
Model: MODEL1
Dependent Variable: resmrg

Number of Observations Read	29
Number of Observations Used	28
Number of Observations with Missing Values	1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	456.63099	456.63099	99755.9	<.0001
Error	26	0.11901	0.00458		
Corrected Total	27	456.75000			

Root MSE	0.06766	R-Square	0.9997
Dependent Mean	18.75000	Adj R-Sq	0.9997
Coeff Var	0.36084		

Parameter Estimates

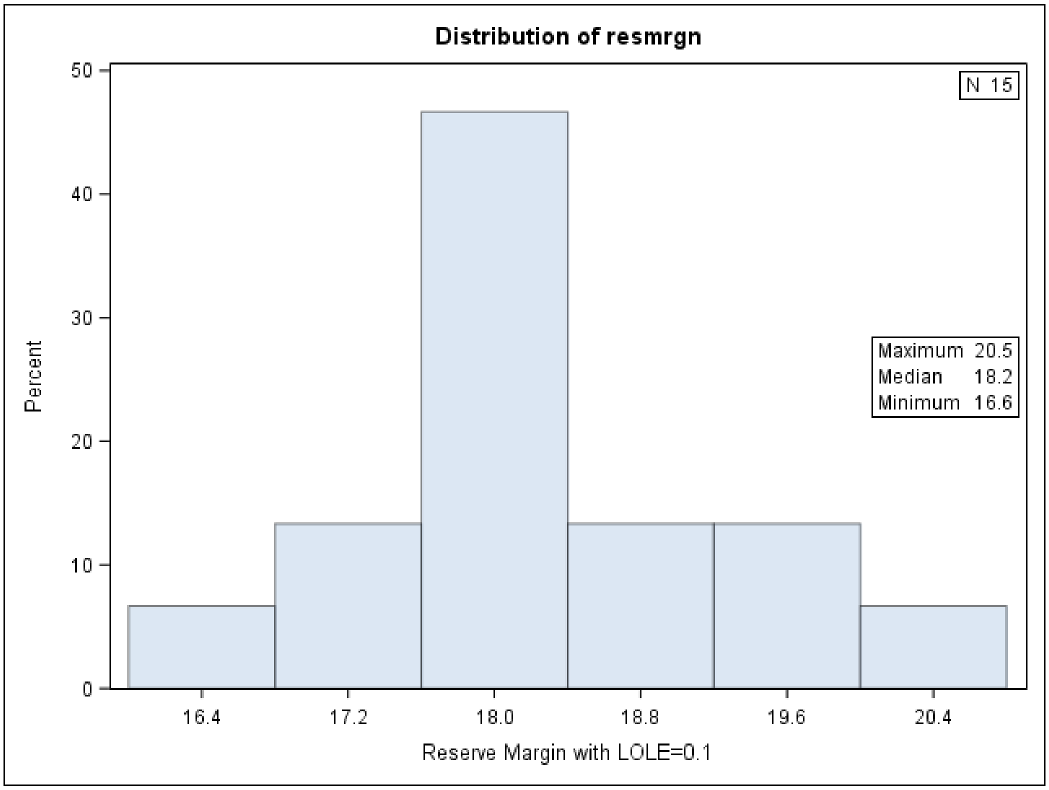
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.84337	0.03387	261.08	<.0001
lnlole	1	-4.00696	0.01269	-315.84	<.0001

The parameter estimates in the function can be used to calculate the reserve margin level associated with an LOLE=0.1. The calculations are as follows:

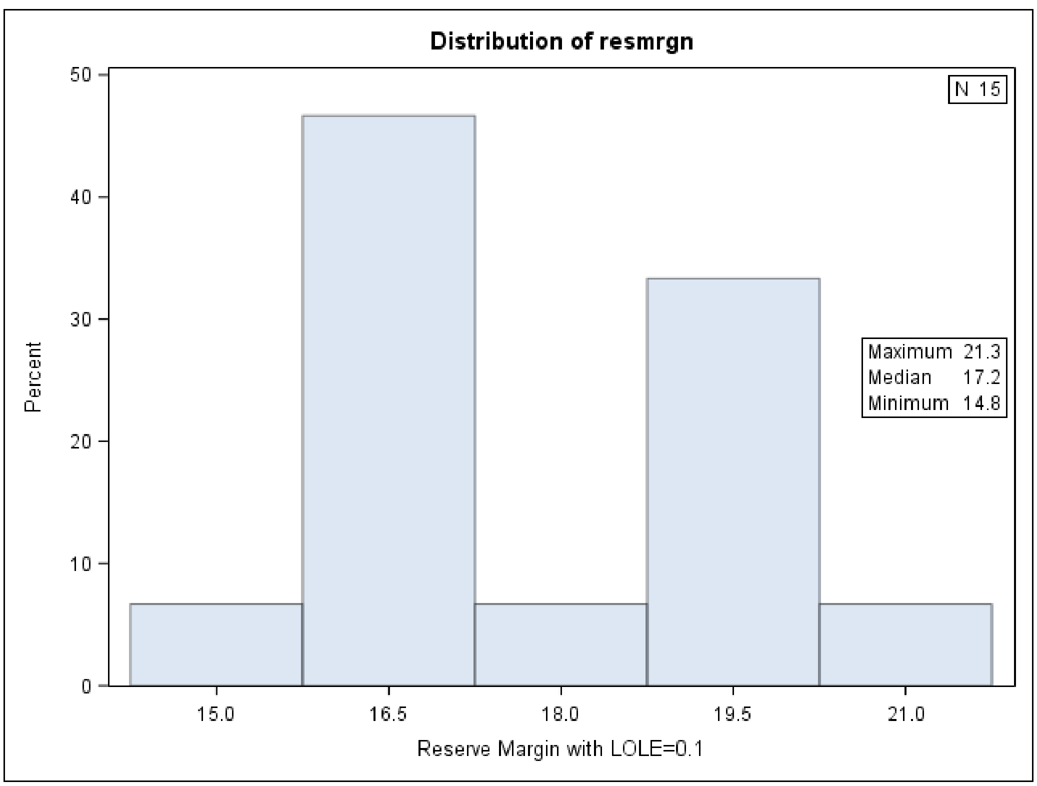
Reserve Margin = a + b * LOG(LOLE)
= 8.84337 – 4.00696 * LOG (0.1)
= 8.84337 – 4.00696 * (-2.30259)
= 18.1

Thus, based on the average LOLE data, an LOLE value of 0.1 requires about an 18.1% reserve margin. The equation can also be used to find the LOLE for a given reserve margin by reversing the solution process. For example, it is easy to show that DESC's base winter reserve margin level of 14% is associated with an LOLE=0.3 or again about a 3 day in 10 LOLE level.

The same log-linear function can be estimated for each year in the study under both the peak method of adjustment and the energy method of adjustment. Once the equations are estimated, their parameters can be used to solve for the reserve margin level associated with an LOLE of 0.1 just as demonstrated above. The following histogram shows the distribution of results for the peak method.



The following histogram shows the results under the energy method of adjustment.



LOLE and the Risk Analysis of Extreme Peaks

The LOLE index may be useful as a measure of the average risk on a system over the entire year but it does not address the risk from peak demands that spike up under severe weather conditions. This can be demonstrated through a simple experiment involving three steps. The first step is to run the LOLE analysis for a year and note the LOLE value. Step two simulates a spike in load on the peak day. Since DESC is concerned with a winter spike in load of around 500 MW, this experiment will increase the peak load by 500. Then the LOLE analysis is run again on the modified load data and the LOLE value is noted. The resulting LOLE value is higher than in step one indicating increased risk over the year. In step 3, the amount of capacity is increased to a level that restores the LOLE value to its original value under step one. The increase in capacity over step one reflects the amount required to offset the increase in risk caused by the spike in peak demand according to LOLE theory.

DESC conducted the experiment described above using the adjusted 2018 load data and a 500 MW spike in peak load. The results of this experiment are summarized in the following table.

Experiment to Analyze Peak Load Increase and Risk			
	Peak Load	Capacity	LOLE
Step 1: Calculate base value of LOLE	4,964	5,900	0.11235
Step 2: Add 500 MW to peak day	5,464	5,900	0.23616
Step 3: Increase Capacity to Restore LOLE	5,464	6,095	0.11234

The LOLE results suggest that an increase of 195 MW in capacity (=6,095-5,900) is sufficient to offset the increase in risk caused by a 500 MW spike in load (=5,464-4,964). This does not seem reasonable. However, the LOLE methodology arrives at this conclusion because it is measuring risk for the entire year and the capacity increase of 195 MW makes every day in the year a little less risky so much so that the unacceptable risk on the peak day is completely offset by the sum of these daily increases.

APPENDIX

Table 1 Annual Summary Information for Adjusted Historical Profiles

"The Energy Method" Historical Profiles Adjusted to 2019 Energy

year	maxmw	summwh
2004	4,532	23,864,178
2005	4,758	23,864,178
2006	4,737	23,864,178
2007	4,803	23,864,178
2008	4,702	23,864,178
2009	4,642	23,864,178
2010	4,471	23,864,178
2011	4,757	23,864,178
2012	4,796	23,864,178
2013	4,636	23,864,178
2014	4,722	23,864,178
2015	4,867	23,864,178
2016	4,658	23,864,178
2017	4,650	23,864,178
2018	4,558	23,864,178

"The Peak Method" Historical Profiles Adjusted to 2019 Seasonal Peak Demands

year	smr_ maxmw	wtr_ maxmw	summwh
2004	4,911	4,964	27,419,072
2005	4,911	4,964	25,821,068
2006	4,911	4,964	26,985,458
2007	4,911	4,964	26,816,776
2008	4,911	4,964	25,576,498
2009	4,911	4,964	25,407,442
2010	4,911	4,964	26,390,123
2011	4,911	4,964	24,798,622
2012	4,911	4,964	25,497,702
2013	4,911	4,964	27,185,234
2014	4,911	4,964	25,686,071
2015	4,911	4,964	24,800,039
2016	4,911	4,964	26,329,200
2017	4,911	4,964	25,951,274
2018	4,911	4,964	25,890,877

Table 2 Capacity Outage Probability Table ("COPT")

Note: LOLP represents the cumulative probability. For example, from the table the probability of 100 MW or more being forced out is about 48.32% while for 900 MW, it's 1.35%.

MW Out	LOLP	MW Out	LOLP	MW Out	LOLP
0	1.0000	530	0.0928	1600	0.0002
10	0.9342	540	0.0902	1700	0.0001
20	0.8588	550	0.0879	1800	0.0000
30	0.8044	560	0.0861	1900	0.0000
40	0.7463	570	0.0844	2000	0.0000
50	0.6969	580	0.0828	2100	0.0000
60	0.6493	590	0.0813	2200	0.0000
70	0.6113	600	0.0798	2300	0.0000
80	0.5670	610	0.0784	2400	0.0000
90	0.5231	620	0.0739	2500	0.0000
100	0.4832	630	0.0691	2600	0.0000
110	0.4497	640	0.0655	2700	0.0000
120	0.4261	650	0.0618	2800	0.0000
130	0.4010	660	0.0586	2900	0.0000
140	0.3803	670	0.0547	3000	0.0000
150	0.3620	680	0.0510	3100	0.0000
160	0.3483	690	0.0472	3200	0.0000
170	0.3358	700	0.0436	3300	0.0000
180	0.3199	710	0.0404	3400	0.0000
190	0.3072	720	0.0375	3500	0.0000
200	0.2946	730	0.0352	3600	0.0000
210	0.2841	740	0.0329	3700	0.0000
220	0.2744	750	0.0308	3800	0.0000
230	0.2663	760	0.0287	3900	0.0000
240	0.2587	770	0.0270	4000	0.0000
250	0.2509	780	0.0253	4100	0.0000
260	0.2432	790	0.0237	4200	0.0000
270	0.2362	800	0.0223	4300	0.0000
280	0.2309	810	0.0210	4400	0.0000
290	0.2262	820	0.0199	4500	0.0000
300	0.2220	830	0.0189	4600	0.0000
310	0.2182	840	0.0178	4700	0.0000
320	0.2151	850	0.0169	4800	0.0000
330	0.2124	860	0.0161	4900	0.0000
340	0.2099	870	0.0153	5000	0.0000
350	0.2017	880	0.0146	5100	0.0000
360	0.1927	890	0.0140	5200	0.0000
370	0.1842	900	0.0135	5300	0.0000
380	0.1761	910	0.0130	5400	0.0000
390	0.1705	920	0.0126	5500	0.0000
400	0.1643	930	0.0122	5600	0.0000
410	0.1573	940	0.0119	5700	0.0000
420	0.1483	950	0.0116	5800	0.0000
430	0.1413	960	0.0110	5900	0.0000
440	0.1330	970	0.0104		
450	0.1260	980	0.0099		
460	0.1202	990	0.0094		
470	0.1149	1000	0.0090		
480	0.1105	1100	0.0042		
490	0.1061	1200	0.0022		
500	0.1023	1300	0.0013		
510	0.0990	1400	0.0006		
520	0.0958	1500	0.0003		

Table 3 LOLE Index by Reserve Margin Based on the "Peak Method" of Adjustment

resmrg	_2004	_2005	_2006	_2007	_2008	_2009	_2010	_2011
12.0	0.43304	0.33493	0.62506	0.49446	0.35865	0.48997	0.83839	0.45379
12.5	0.38234	0.28952	0.54329	0.43004	0.31434	0.42833	0.73506	0.39627
13.0	0.33579	0.24906	0.47080	0.37403	0.27465	0.37130	0.64482	0.34655
13.5	0.29427	0.21524	0.40965	0.32541	0.23864	0.32148	0.56614	0.30450
14.0	0.25945	0.18814	0.35898	0.28510	0.20909	0.28084	0.49862	0.27099
14.5	0.22773	0.16403	0.31291	0.24937	0.18232	0.24306	0.43714	0.24048
15.0	0.19996	0.14384	0.27486	0.21966	0.15906	0.21196	0.38459	0.21339
15.5	0.17568	0.12679	0.24355	0.19491	0.13993	0.18567	0.33983	0.19098
16.0	0.15441	0.11227	0.21634	0.17372	0.12290	0.16291	0.30107	0.17029
16.5	0.13568	0.09938	0.19270	0.15497	0.10799	0.14351	0.26625	0.15038
17.0	0.11934	0.08851	0.17207	0.13810	0.09560	0.12756	0.23707	0.13313
17.5	0.10555	0.07983	0.15480	0.12416	0.08519	0.11502	0.21279	0.11820
18.0	0.09296	0.07167	0.13861	0.11035	0.07558	0.10297	0.18781	0.10352
18.5	0.08209	0.06410	0.12357	0.09739	0.06721	0.09244	0.16592	0.09087
19.0	0.07391	0.05802	0.11111	0.08749	0.06078	0.08396	0.14894	0.08126
19.5	0.06554	0.05169	0.09799	0.07714	0.05409	0.07458	0.13103	0.07128
20.0	0.05784	0.04539	0.08579	0.06728	0.04766	0.06578	0.11438	0.06211
20.5	0.05115	0.03956	0.07476	0.05872	0.04194	0.05798	0.10023	0.05441
21.0	0.04541	0.03469	0.06558	0.05162	0.03704	0.05088	0.08837	0.04816
21.5	0.03935	0.02986	0.05648	0.04460	0.03197	0.04389	0.07692	0.04207
22.0	0.03466	0.02608	0.04945	0.03922	0.02806	0.03839	0.06781	0.03737
22.5	0.03064	0.02290	0.04340	0.03455	0.02467	0.03348	0.05980	0.03310
23.0	0.02702	0.01995	0.03807	0.03043	0.02158	0.02921	0.05265	0.02921
23.5	0.02368	0.01740	0.03347	0.02683	0.01882	0.02549	0.04628	0.02578
24.0	0.02087	0.01544	0.02987	0.02391	0.01663	0.02254	0.04115	0.02305
24.5	0.01836	0.01370	0.02664	0.02125	0.01467	0.01990	0.03648	0.02043
25.0	0.01628	0.01223	0.02381	0.01889	0.01304	0.01769	0.03249	0.01814
25.5	0.01452	0.01099	0.02140	0.01688	0.01164	0.01590	0.02902	0.01617

resmrg	_2012	_2013	_2014	_2015	_2016	_2017	_2018
12.0	0.34195	0.47973	0.50334	0.68108	0.59148	0.47691	0.60222
12.5	0.29966	0.41645	0.44353	0.59311	0.51914	0.41560	0.52399
13.0	0.26082	0.36145	0.38897	0.51658	0.45567	0.36194	0.45509
13.5	0.22690	0.31301	0.33929	0.45024	0.40182	0.31619	0.39603
14.0	0.19992	0.27391	0.29755	0.39668	0.35717	0.27895	0.34868
14.5	0.17554	0.23941	0.25920	0.34994	0.31687	0.24577	0.30656
15.0	0.15492	0.21057	0.22644	0.30979	0.28188	0.21875	0.27134
15.5	0.13721	0.18673	0.19922	0.27610	0.25044	0.19479	0.24061
16.0	0.12178	0.16605	0.17604	0.24680	0.22174	0.17309	0.21397
16.5	0.10773	0.14804	0.15529	0.22118	0.19539	0.15444	0.19091
17.0	0.09539	0.13315	0.13729	0.19884	0.17194	0.13755	0.17067
17.5	0.08499	0.12083	0.12224	0.17871	0.15189	0.12279	0.15283
18.0	0.07510	0.10732	0.10825	0.15769	0.13273	0.10798	0.13558
18.5	0.06636	0.09521	0.09596	0.13974	0.11612	0.09488	0.11990
19.0	0.05970	0.08596	0.08641	0.12508	0.10348	0.08500	0.10756
19.5	0.05282	0.07554	0.07654	0.10919	0.09103	0.07486	0.09461
20.0	0.04635	0.06568	0.06726	0.09460	0.07975	0.06513	0.08234
20.5	0.04084	0.05736	0.05926	0.08252	0.07026	0.05697	0.07183
21.0	0.03604	0.05022	0.05239	0.07242	0.06244	0.05020	0.06297
21.5	0.03114	0.04315	0.04539	0.06268	0.05464	0.04343	0.05441
22.0	0.02742	0.03774	0.03978	0.05523	0.04853	0.03821	0.04792
22.5	0.02429	0.03320	0.03498	0.04891	0.04311	0.03378	0.04234
23.0	0.02141	0.02927	0.03073	0.04334	0.03819	0.02991	0.03734
23.5	0.01875	0.02582	0.02694	0.03824	0.03359	0.02647	0.03281
24.0	0.01662	0.02293	0.02385	0.03406	0.02979	0.02358	0.02920
24.5	0.01465	0.02039	0.02107	0.03040	0.02631	0.02086	0.02603
25.0	0.01301	0.01830	0.01868	0.02729	0.02330	0.01862	0.02338
25.5	0.01162	0.01656	0.01668	0.02454	0.02071	0.01674	0.02094

Table 4 LOLE Index by Reserve Margin Based on the "Energy Method" of Adjustment

resmrg	_2004	_2005	_2006	_2007	_2008	_2009	_2010	_2011
12.0	0.29226	0.27686	0.46937	0.37424	0.37084	0.57333	1.04027	0.59745
12.5	0.25781	0.24348	0.40882	0.32623	0.32538	0.50346	0.91209	0.52065
13.0	0.22587	0.21116	0.35660	0.28759	0.28646	0.44189	0.79405	0.44877
13.5	0.19849	0.18237	0.30852	0.25069	0.25061	0.38121	0.69132	0.38656
14.0	0.17449	0.15778	0.26912	0.21984	0.22108	0.33125	0.60640	0.34001
14.5	0.15279	0.13840	0.23629	0.19330	0.19472	0.28873	0.53515	0.30082
15.0	0.13478	0.12105	0.20799	0.17042	0.17105	0.25093	0.47095	0.26634
15.5	0.11819	0.10705	0.18208	0.14913	0.15117	0.21842	0.41459	0.23882
16.0	0.10349	0.09510	0.16150	0.13151	0.13256	0.19121	0.36917	0.21311
16.5	0.09128	0.08465	0.14290	0.11640	0.11685	0.16736	0.32648	0.19115
17.0	0.08036	0.07508	0.12686	0.10361	0.10242	0.14794	0.29007	0.17233
17.5	0.07035	0.06714	0.11360	0.09235	0.09040	0.13154	0.25950	0.15329
18.0	0.06245	0.05917	0.10174	0.08258	0.07997	0.11813	0.23035	0.13646
18.5	0.05527	0.05246	0.09068	0.07359	0.07076	0.10696	0.20583	0.12126
19.0	0.04902	0.04715	0.08089	0.06592	0.06284	0.09665	0.18357	0.10816
19.5	0.04339	0.04144	0.07225	0.05866	0.05519	0.08642	0.16144	0.09409
20.0	0.03858	0.03645	0.06346	0.05129	0.04901	0.07700	0.14256	0.08244
20.5	0.03399	0.03215	0.05575	0.04520	0.04322	0.06871	0.12592	0.07209
21.0	0.03004	0.02826	0.04905	0.03952	0.03826	0.05976	0.11022	0.06279
21.5	0.02662	0.02449	0.04266	0.03464	0.03365	0.05210	0.09588	0.05458
22.0	0.02324	0.02142	0.03701	0.03016	0.02963	0.04553	0.08401	0.04785
22.5	0.02037	0.01871	0.03249	0.02647	0.02593	0.03948	0.07385	0.04192
23.0	0.01807	0.01646	0.02840	0.02352	0.02276	0.03440	0.06504	0.03717
23.5	0.01593	0.01448	0.02498	0.02071	0.02010	0.03014	0.05751	0.03311
24.0	0.01393	0.01314	0.02214	0.01825	0.01774	0.02646	0.05108	0.02906
24.5	0.01234	0.01144	0.01940	0.01616	0.01562	0.02324	0.04516	0.02647
25.0	0.01089	0.01009	0.01765	0.01450	0.01378	0.02067	0.04013	0.02360
25.5	0.00965	0.00897	0.01565	0.01293	0.01248	0.01832	0.03577	0.02114

resmrg	_2012	_2013	_2014	_2015	_2016	_2017	_2018
12.0	0.36312	0.27772	0.21390	0.31315	0.61847	0.55622	0.67135
12.5	0.31640	0.24410	0.18773	0.27953	0.53751	0.48258	0.58840
13.0	0.27804	0.21059	0.16401	0.24748	0.47098	0.42163	0.50893
13.5	0.24092	0.18198	0.14117	0.21822	0.41044	0.36520	0.44279
14.0	0.21091	0.15843	0.12199	0.19151	0.36065	0.32005	0.39064
14.5	0.18544	0.13714	0.10532	0.16994	0.32024	0.28051	0.34284
15.0	0.16342	0.12047	0.09156	0.14794	0.28384	0.24857	0.30292
15.5	0.14489	0.10550	0.07972	0.12813	0.25354	0.22082	0.27042
16.0	0.12929	0.09362	0.06970	0.11102	0.22724	0.19688	0.24002
16.5	0.11518	0.08392	0.06092	0.09710	0.20343	0.17686	0.21370
17.0	0.10310	0.07538	0.05395	0.08428	0.18037	0.15723	0.19195
17.5	0.09167	0.06724	0.04780	0.07384	0.15995	0.14018	0.17022
18.0	0.08209	0.06016	0.04280	0.06534	0.14167	0.12551	0.15198
18.5	0.07224	0.05382	0.03849	0.05840	0.12386	0.11142	0.13484
19.0	0.06387	0.04805	0.03461	0.05205	0.10964	0.09894	0.11951
19.5	0.05628	0.04225	0.03114	0.04652	0.09580	0.08692	0.10528
20.0	0.04945	0.03739	0.02756	0.04124	0.08369	0.07635	0.09206
20.5	0.04316	0.03257	0.02445	0.03680	0.07310	0.06677	0.08070
21.0	0.03787	0.02853	0.02150	0.03268	0.06404	0.05850	0.07032
21.5	0.03308	0.02473	0.01866	0.02917	0.05663	0.05072	0.06119
22.0	0.02897	0.02153	0.01621	0.02557	0.04960	0.04460	0.05369
22.5	0.02546	0.01899	0.01421	0.02226	0.04372	0.03902	0.04747
23.0	0.02213	0.01649	0.01227	0.01959	0.03904	0.03424	0.04180
23.5	0.02008	0.01446	0.01076	0.01718	0.03463	0.03031	0.03691
24.0	0.01780	0.01289	0.00937	0.01493	0.03094	0.02702	0.03276
24.5	0.01582	0.01148	0.00824	0.01309	0.02746	0.02403	0.02916
25.0	0.01404	0.01026	0.00749	0.01153	0.02441	0.02147	0.02624
25.5	0.01246	0.00907	0.00652	0.01022	0.02153	0.01922	0.02323